The Fall and Rise of Immigrant Employment During the Covid-19 Pandemic

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Abstract: Employment rates fell dramatically between March and April 2020 as the initial shock of the Covid-19 pandemic reverberated through the U.S. labor market. This paper uses data from the CPS Basic Monthly Files to document that the employment decline was particularly severe for immigrants. Historically, immigrant men are more likely to work than native men. The pandemic-related labor market shock eliminated the immigrant employment advantage. After this initial precipitous drop, however, the employment recovery through June 2021 was much stronger for immigrants, and particularly for undocumented immigrants. The steep drop in immigrant employment at the start of the pandemic occurred partly because immigrants were less likely to work in jobs that could be performed remotely and suffered disproportionate employment losses as only workers with remotable skills were able to continue working from home. The stronger employment recovery of undocumented immigrants, relative to that experienced by natives or legal immigrants, is mostly explained by the fact that undocumented workers were not eligible for the generous unemployment insurance (UI) benefits offered to workers during the pandemic.

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George J. Borjas and Hugh Cassidy*

1. Introduction

Within a period of less than 2 months, the Covid-19 pandemic produced dramatic and historic aftershocks throughout the U.S. labor market. In December 2020, the unemployment rate stood at a near-record low of 3.5 percent (a level not seen since the early 1950s), and the number of persons in the workforce stood at a record high of 158.8 million. The first positive Covid-19 test result in the United States (in the state of Washington) was not confirmed until February 21, 2020. In New York City, which would soon become an epicenter of the pandemic, the first positive test result was not confirmed until February 23. The first (reported) Covid-related death occurred near Seattle on February 29. The situation deteriorated very quickly and dramatically after that.

In March 2020, federal, state, and local governments reacted to the spread of the virus by adopting measures that "paused" economic activity in many sectors. The economic lockdown had swift employment repercussions. The weekly number of new claims for unemployment benefits had hovered at slightly above 200,000 in both January and February 2020 (as it had throughout the entire 2019 calendar year). This number, however, increased dramatically to a historic high of 3.3 million in the week ending March 21 and skyrocketed to 6.9 million in the week ending March 28. During the month of April 2020, 20.1 million additional workers filed

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for jobless claims.[1] Not surprisingly, the unemployment rate rose to 14.7 percent by April 2020, a level of unemployment not witnessed since the Great Depression.

The pandemic-related economic pause and lockdown differentially affected the employment opportunities of persons working in different sectors. Workers whose jobs could be performed remotely from home, such as teachers and customer support specialists, continued to work from their home office. Workers who provided essential services, such as health care professionals and grocery store clerks, continued their usual work routine. But job opportunities for many other workers outside these protected groups quickly evaporated.

This sudden and historic change in employment opportunities ensures that a great deal of research will be conducted as we attempt to understand the consequences of the labor market disruptions sparked by the pandemic.[2] This paper contributes to the literature by focusing on how the labor market shock differentially affected immigrants and natives.

Immigrants make up an increasingly important fraction of the U.S. workforce. In 1980, immigrants comprised only 6.6 percent of the workforce. By 2019, the immigrant share had risen to 17.6 percent. It is well known that immigrants have historically had different employment rates than their native-born counterparts (Borjas, 2017; Nekoei, 2013). Figure 1 illustrates the long-term (pre-pandemic) trend in the employment rates of various groups using data from the Current Population Surveys (CPS). In 2005, the employment rate of immigrant men was almost 6 percentage points *higher* than that of native men. The immigrant-native gap remained even during the Great Recession that followed the financial crisis of 2008. Although the employment

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[1] These data are available at https://oui.doleta.gov/unemploy/claims.asp.

[2] The work has already started. See Cajner et al (2020) for a study in the American context and Von Gaudacker et al (2020) for an examination of the Netherlands experience. Other studies that look at impacts outside the labor market include Bergen, Herkenhoff, and Mongey (2020), Chatterji and Li (2020), and Lang, Wang, and Yang (2020).

rate of both groups declined, the immigrant employment advantage was still over 5 percentage points in 2010. By 2019, at the peak of the economic boom, the immigrant employment advantage still held steady at about 6 percentage points.

The figure also shows that immigrant women have historically had *lower* employment rates than their native counterparts. This employment disadvantage has remained roughly constant in the past decade. It was about 9 percentage points at the bottom of the Great Recession in 2010 and it was still 9 percentage points at the peak of the economic boom in 2019.

Our analysis uses data from the CPS Basic Monthly files to document the disproportionately adverse impact that the initial phase of the COVID-19 pandemic had on the employment of immigrants. Not surprisingly, the employment rate of both natives and immigrants declined dramatically as the aftershocks of the pandemic spread through the labor market. The initial adverse employment effect, however, was far larger for foreign-born workers. The employment advantage that immigrant men had long enjoyed completely evaporated. In April 2020, the employment rate of both immigrant and native men stood at about 72.5 percent.

Despite this remarkable downturn in the relative employment opportunities of immigrants in a single month, the economic recovery that followed (through June 2021, when our sample period ends) also affected immigrants and natives differentially. Specifically, the employment rate of immigrant men increased at a much faster rate than that of native men after the initial shock. By June 2021, the pre-pandemic employment advantage of immigrant men had been reestablished, with the immigrant employment rate standing at 84.9 percent and that of natives at 78.4 percent, a gap of 6.5 percentage points.

This paper provides a detailed examination of both the much steeper drop in the employment opportunities of immigrants in the critical months of March-April 2020, and of the much faster rise in immigrant employment opportunities in the subsequent year. We focus on two variables that might account for the differential trends. Part of the larger adverse effect that the pandemic initially had on immigrant employment can be traced to the fact that immigrants and natives tend to do different jobs. Immigrants were less likely to be employed in jobs that could be done remotely prior to the pandemic, and suffered accordingly as the economic lockdown allowed workers with "remotable" skills to work from home.

Using data from the Department of Labor's O*NET that enumerates the tasks performed by different occupations, we construct an index of "remotability" for each occupation. The evidence suggests that the pre-pandemic immigrant-native difference in the level of this index explains about a third of the steeper decline in employment opportunities that immigrants experienced between March and April 2020.

Our analysis of the subsequent recovery focuses on the potentially different role played by unemployment insurance (UI) benefits for a relatively large subsample of the immigrant population. Undocumented workers were not eligible for the generous UI benefits that the federal government and many states offered to workers who lost their jobs during the pandemic months. Using imputation methods that are now commonly applied to construct an immigration status variable for foreign-born persons in micro data (Borjas, 2017, Borjas and Cassidy, 2019, Churchill, Mackay, and Tan, 2021, Cho, 2019), we document the very distinct employment trends exhibited by the group of undocumented workers. In particular, the employment rate of undocumented men dropped by nearly 14.4 percentage points between March and April 2020, as compared to a 11.9 percentage point drop for legal immigrant men, and a 7.9 percentage points drop for native men. In contrast, the employment rate of undocumented men rose the most in the subsequent year. By June 2021, the employment rate of undocumented men was 93.6 percent, that of legal immigrants stood at 85.1 percent, and that of natives had increased to "only" 79.3 percent.

Because the distinct employment trends exhibited by undocumented immigrants during the recovery period were not affected by the disincentive effects of UI benefits, the comparison of the employment trends among natives, legal immigrants, and undocumented immigrants allows us to exploit inter-state differences in the level of UI benefits to retrieve estimates of the causal impact of unemployment insurance on the employment recovery. The evidence suggests that the disincentive effects of the UI benefits are large, and that the increase in the employment rate of native workers would have been about 7 percentage points larger in the absence of such benefits.

2. Data and Descriptive Evidence

Our analysis of how the Covid-19 pandemic differentially affected employment opportunities for immigrants and natives uses the CPS Basic Monthly files, downloaded from the Integrated Public Use Microdata Series (IPUMS) (Flood et al, 2020). Throughout the analysis, we analyze the subsample of persons aged 21-64, who are not enrolled in school, and are not in the Armed Forces.

We initially document the impact of the pandemic on the labor market by illustrating the trend in the monthly employment rate between January 2019 and June 2021 (by gender).[3] As

[3] The employment rate is given by the fraction of the relevant population that is working. Our definition of "work" is based on a person's employment status in the reference week of the Basic Monthly sample. We use the IPUMS variable reporting a person's employment status (*empstat*) and classify a person as working if he or she is "at work" or "has job, not at work last week." Our definition of employment is identical to that used by the BLS, which states that "individuals also are counted as employed if they have a job at which they did not work during the survey week" (U.S. Bureau of Labor Statistics, 2021). Our results are not qualitatively changed if we define employment as only being "at work."

suggested by our earlier discussion, Figure 2 shows that immigrant men were more likely to be employed than native men throughout 2019, while immigrant women were less likely to be employed than native women. Note that the gender-specific paths of employment rates for immigrants and natives are roughly parallel in calendar year 2019, with all groups experiencing the same seasonal decline in employment during the summer months.

The long-standing employment advantage enjoyed by immigrant men, however, changed drastically because of the employment losses produced by the initial reaction to the pandemic. The data reveal a somewhat steeper decline in the employment rate of immigrant men, from 88.8 to 86.6 percent between February and March 2020, as compared to a drop of 0.5 percentage points for native men in the same period (the native employment rate fell from 81.0 to 80.5 percent). The relative decline in the employment rate of immigrant men accelerated dramatically between March and April, as the initial policy response to the pandemic, including various types of lockdowns, business closures, and travel restrictions, began to reverberate through the labor market. The employment rate of immigrant men fell by an additional 14 percentage points between March and April, as compared to an 8-point drop for natives. In fact, this monthly decline in immigrant employment was so precipitous that April 2020 became the first month in the 21st century in which the employment advantage long enjoyed by immigrant men effectively disappeared. In April 2020, the employment rate of both immigrant and native men stood at about 72.5 percent.

The figure also reveals an equally dramatic recovery in the (relative) employment rate of immigrant men between May 2020 and October 2020. The employment rate of immigrant men rose by over 9 percentage point during those months (from 75.4 to 84.5 to percent), as compared to an increase of only 4 percentage points for native men (from 74.2 to 78.2 percent). By the end of calendar year 2020, therefore, the pre-pandemic employment advantage enjoyed by immigrant men had been reestablished, and that advantage persisted throughout the first half of 2021 (when our sample period ends).

The differences in the employment trends of immigrant women and native women seem less striking (at least superficially). In fact, the trend lines for the employment rates of the two groups tend to be roughly parallel between January and April 2020. Both groups began to experience a decline in their employment rate between February and March 2020, with the employment rate for immigrant women falling by about 2.2 percentage points as compared to a 1-point drop for native women. Similarly, the decline for immigrant women between March and April was slightly larger than for natives (10.9 versus 9.8 percentage points). Note, however, that immigrant women have lower employment rates than native women, so that the *percent* decline in female immigrant employment resulting from the pandemic was quite large. The pre-pandemic (February 2020) employment rate of immigrant women was 63.9 percent. By April 2020, their employment rate had fallen to 50.8 percent, so that their employment rate fell by about 20 percent. In contrast, the employment rate of native women fell by 14 percent.

As with immigrant men, there was substantial recovery in the (relative) employment rate of immigrant women prior to the end of calendar year 2020. By December 2020, the employment advantage enjoyed by native women over immigrant women was over 11 percentage points, a slight increase in the 9 to 10 percentage point advantage that existed prior to the pandemic.

It is useful to decompose the changes in the employment rate revealed in Figure 2 into its key components. Let E_t be the number of persons in a particular population (e.g., natives) employed at time t, N_t be the number who are not employed, and P be the (assumed constant) population. Further, let F_t be the number of persons who were not employed at time *t*, but who found a job by time *t*+1. Similarly, let L_t be the number of persons who were employed at time *t* and had lost their job by time *t*+1. The change in the employment rate observed between times *t* and *t*+1 can be written as:

$$\frac{E_t - E_{t-1}}{P} = \frac{(F_t - L_t)}{P} = \frac{N_t}{P} \cdot \frac{F_t}{N_t} - \frac{E_t}{P} \cdot \frac{L_t}{E_t} = (1 - \pi_t) f_t - \pi_t \ell_t, \tag{1}$$

where π_t is the employment rate at time *t*; f_t is the job-finding rate, or the fraction of persons out of work who find a job by time *t*+1; and ℓ_t is the job-loss rate, or the fraction of employed persons who are not working by the next period. Equation (1) shows that the month-to-month change in employment rates illustrated in Figure 2 is a weighted average of the job-finding rate and the job-loss rate.

The sampling rotation used by the CPS—where a person is interviewed for 4 continuous months, is not interviewed for the next 8 months, and is then interviewed again for an additional 4 months—allows us to calculate the job-finding and job-loss rates for the immigrant and native populations. Specifically, the sampling rotation allows us to observe changes in the employment status of the large subsample of persons who happen to appear in the two consecutive CPS surveys for months *t* and *t*+1.[4] Figure 3 shows the trends in the job-loss rate between January 2019 and June 2021, while Figure 4 shows the respective trends in the job-finding rate.

[4] We used the matching variable created by IPUMS (*cpsidp*) to match specific persons across CPS cross-sections.

Consider initially the trends in the job-loss rate. Before the pandemic, the job-loss rates of immigrant men and native men were roughly the same. In the 2019 calendar year, for example, the average (monthly) job-loss rate of immigrant and native men was 2.4 and 2.3 percent, respectively. Note, however, that the relative job-loss rate for immigrant men began to increase in February 2020 (measuring job losses between February and March) and shot up dramatically in March 2020 (measuring job losses between March and April), when the job-loss rate increased to 11.9 percent for natives and to 17.5 percent for immigrants. Given the fact that immigrant men had very high employment rates prior to the pandemic, equation (1) suggests that the key reason for the substantial drop in the relative employment rate of immigrant men was the sizable increase in their job-loss rate.

Figure 3 also reveals that the job-loss rates for immigrant and native men returned to their pre-pandemic parity by June 2020, although both rates remained at a slightly higher level than in the pre-pandemic period. Between June 2020 and May 2021, the average job-loss rates of immigrant men and native men were 3.4 and 2.9 percent, respectively.

The top panel of Figure 4 illustrates the analogous trends in the job-finding rates for immigrant and native men. Interestingly, the data reveal that the job-finding rate for immigrant men was substantially higher than that of native men in the pre-pandemic 2019 calendar year.[5] The average job-finding rate in calendar 2019 was 17.3 percent for immigrants and 9.7 percent for natives. The job-finding rate of both groups increased dramatically immediately after the March-April 2020 negative employment shock. Between April and May 2020, for example, the job finding rate of immigrants increased to 26.4 percent while that of natives increased to 17.0

[5] Albert (2020) examines the immigrant-native difference in job-finding rates in the context of a job search model.

percent, so that the immigrant-native *gap* in job-finding rates was not greatly affected by the initial labor market response to the pandemic. Moreover, this immigrant advantage in job-finding rates persisted through the rest of the sample period.

The figures also illustrate the job-loss and job-finding rates of immigrant and native women. Prior to the pandemic, the job loss rate for immigrant women was slightly higher than that of native women. In calendar year 2019, for example, the job-loss rate was 4.4 percent for immigrants and 3.2 percent for natives. The (relative) job loss rate for immigrant women increased dramatically in March 2020, however. The job-loss rate for immigrant women in that month rose to 23.0 percent, while the rate for native women rose to 15.2 percent, a gap of almost 8 percentage points. In short, the comparison of the trends illustrated in Figure 3 show that—regardless of gender—many immigrant workers (relative to natives) found it difficult to hold on to their existing jobs in the crucial period between March and April 2020.

Finally, the bottom panel of Figure 4 shows the trend in the job-finding rates for immigrant and native women. Although the trends in the job finding rates for both native and immigrant women are noisier than the male trends, it is evident that prior to the pandemic the job-finding rates of immigrant and native women are roughly the same (in fact, the average monthly job finding rate during the 2019 calendar year is 7.5 percent for immigrant women and 7.3 percent for native women). The figure also suggests that the job-finding rates for the two groups are again roughly similar after the initial shock (for example, the average monthly job-finding rate between June 2020 and June 2021 is 8.5 percent for immigrant women and 8.3 percent for native women). The only noticeable difference in job-finding rates between the two groups appears between April and May 2020, when the job-finding rate of native women increased substantially (to 13.3 percent), while that of immigrant women had a somewhat smaller increase (to 10.9 percent).

For expositional convenience, much of the empirical analysis presented in the remainder of this paper focuses on the data contained in the Basic Monthly samples between January 2019 and June 2021. We will often pool the data from these cross-sections. Table 1 reports summary statistics from this pooled data for each of the four demographic groups under analysis. Not surprisingly, the summary statistics imply that immigrants are older than natives, tend to be at the extremes of the distribution of educational attainment, and are more likely to reside in metropolitan areas and cluster in a relatively small number of states.

3. Regression Results

This section uses data from the pooled CPS Basic Monthly files from January 2019 to June 2021 to document the determinants of the historic changes in employment observed immediately after the pandemic hit the United States. We begin by estimating the following generic regression model in the pooled data:

$$y_{it} = \theta_c + \theta_p + \alpha M_i + \lambda_p(\theta_p \times M_i) + \beta X_{it} + \epsilon \quad (2)$$

where y_{it} is a measure of employment status for person *i* in month *t*; θ_c is a vector of calendar month fixed effects (i.e., January, February, etc.) that account for seasonal variation in employment; θ_p is a vector of pandemic month fixed effects that represent specific post-January 2020 periods (e.g., March 2020, April 2020, etc.); M_i is an indicator variable set to unity if worker *i* is an immigrant; and *X* is a vector of socioeconomic characteristics (discussed below).

The coefficient vector θ_p in equation (2) gives the adjusted employment rate of natives in pandemic month p. The coefficient vector λ then gives the corresponding difference in the employment status between immigrants and natives for each month during the pandemic. The regression model in (2), therefore, enables us to easily summarize the (relative) employment trends in the data, and to document how the immigrant-native gap changes after we adjust for the different socioeconomic characteristics of the two samples. The goal of the regression analysis is to isolate which (if any) of the differences in socioeconomic characteristics explains the disproportionately adverse impact of the Covid-19 pandemic on the employment opportunities of immigrants. All regressions are estimated using ordinary least squares, use the CPS sampling weights, and are estimated separately in the samples of men and women.

Table 2 reports the estimates of the relevant coefficients in the vector λ from regressions estimated in the male (columns 1-2) and female (columns 3-4) samples, where the dependent variable simply indicates if person *i* is working at time *t* (i.e., the regression is an employment rate regression). Column 1 excludes the vector of demographic variables *X*, thus reproducing the relative differences observed in the raw data. In the first half of 2020, each fixed effect θ_p in the pandemic period is defined as a month, with calendar year 2019 being the omitted period. For brevity, from July 2020 onward, we group months into quarters.

The regression coefficients show that immigrant men enjoyed an employment advantage of 6.7 percentage points prior to the pandemic; that this advantage declined slightly in March; and effectively disappeared in April when the pandemic hit. By April 2020, the immigrant employment rate was only 0.5 percentage points above that of natives. The regression also shows the values of the λ fixed effects through the rest of calendar year 2020 and the first half of 2021.

Note that the relative employment advantage enjoyed by immigrant men prior to the pandemic had effectively returned to its pre-pandemic level by October 2020.

Column 2 adds a vector of demographic characteristics *X* to the baseline specification. This vector includes age (introduced as a cubic), educational attainment fixed effects, indicator variables for marital status and the presence of children aged five or under, state fixed effects, and a variable indicating if the person resides in a metropolitan area. The addition of these controls has little effect on the coefficients and does not change the conclusions from column 1 in any meaningful way. Even after controlling for differences in human capital and other characteristics, male immigrants enjoyed a 6.4 percentage point higher employment rate than natives in calendar year 2019. By April 2020, that gap had narrowed by 6.2 percentage points, resulting in a nearly identical (adjusted) employment rate between native and immigrant men in April 2020. The recovery returned the (adjusted) employment advantage enjoyed by immigrant men to its pre-pandemic level by October 2020.

Columns 3 and 4 replicate the regression analysis in the female sample. Unlike in the male sample, female immigrants had a much lower (8.5 percentage points) employment rate than native women prior to the pandemic in calendar year 2019. Like immigrant men, however, immigrant women experienced a much larger reduction in their employment rate in the early stages of the pandemic. By April 2020, the employment rate of immigrant women fell by 3.1 percentage points more than that of native women. Note that the employment gap between immigrant and native women effectively returned to its pre-pandemic "equilibrium" by the spring of calendar year 2021.

Column 4 of Table 2 adds controls for the demographic characteristics. Although the pre-pandemic employment gap between immigrant and native men was not especially sensitive to these demographic controls, this is not the case for the employment gap between immigrant and native women, which narrows by more than half to 3.7 percentage points in the presence of these controls. However, the change in the employment gap between January and April 2020 is only mildly affected by the inclusion of the control variables.

As emphasized earlier, the relative immigrant-native employment gap for both men and women eventually returned to its pre-pandemic level for both men and women (with the recovery taking somewhat longer for women). Given the very large relative drop in employment rates that *all* immigrants experienced between March and April 2020, the data suggests that the labor market recovery of immigrants proceeded more quickly than that of natives. We will initially focus the discussion on the employment losses suffered by immigrants at the onset of the pandemic, but we will provide a detailed analysis of the employment recovery in Section 6.

To better understand the determinants of the drop in the employment rates in the spring of calendar year 2020, especially during the critical early pandemic period, we explore the determinants of the job-loss rate of immigrants and natives, and document how these rates are related to both demographic and employment characteristics. Our dependent variable in the job-loss analysis is ℓ_{it}, which is set to unity if worker i was employed in month t but was not employed in month t+1. For expositional convenience, a reference to a job loss occurring in month t refers to the job loss that occurred between month t and month t+1.

We again define the period between January 2019 and December 2019 to be the "baseline" pre-pandemic period. Our regression analysis then explores the determinants of what happened to the (relative) rates of job loss in each of the subsequent months through May 2020. We then estimate the following generic regression model in the pooled data:

$$\ell_{it} = \theta_c + \theta_p + \alpha M_i + \lambda_p(\theta_p \times M_i) + \beta_p(\theta_p \times X_{it}) + \epsilon \tag{3}$$

where θ_c again represents a vector of calendar month fixed effects (to adjust for seasonal variation in job-loss rates); θ_p is a vector of pandemic month fixed effects; and the vector of coefficients λ_p captures the variation in the immigrant-native gap in job-loss rates during the pandemic. Note that all the variables in the vector *X* are interacted with the pandemic month fixed effects to allow for the possibility that the impact of these demographic variables also changed during the pandemic.

The results from the estimation of equation (3), separately for men and women, are shown in Table 3. All specifications include the vector of demographic variables defined earlier (i.e., age, education, marital status, presence of young children, state of residence, and a metropolitan area indicator). Prior to the onset of the pandemic, immigrant men had a 0.6 percentage point lower probability of job loss than native men (column 1), while immigrant women had a 1.3 percentage point higher probability of job loss relative to native women (column 4). The data suggest only a slight change in the immigrant-native job-loss gap in February 2020 for both men and women.

However, in March 2020, both immigrant men and women experienced a large increase in their risk of job loss relative to demographically similar natives. For men, the job-loss gap rose by a substantial 5.7 percentage points, while the increase for women was even greater (6.5 percentage points). In short, the spike in job loss in the critical early month of the pandemic (March-April 2020) was significantly greater for immigrants than natives, and this sizable gap cannot be explained by differences in demographic characteristics between the groups.

The remaining columns of Table 3 examine the potential importance of differences in *job characteristics*, particularly industry and occupation, as factors that might explain the widening gap between immigrants and natives in the probability of job loss as the pandemic shocked the labor market.[6] In particular, columns 2 and 4 add a set of industry fixed effects. The inclusion of these fixed effects barely changes the jump in the immigrant-native gap in the job-loss probability for both men and women. Columns 3 and 6 add a vector of occupation fixed effects. The adjustment for occupational differences between the groups reduces the impact of the pandemic on the immigrant-native difference in the job-loss rate, reducing it to 3.6 percentage points for men and 4.3 percentage points for women. Put differently, although a significant portion of the pandemic-induced increase in the immigrant-native difference in job-loss rates in the critical month of March 2020 remains unexplained, employment characteristics (particularly occupation) appear to be significant contributors to the widening of the job-loss gap at the onset of the pandemic.

The sensitivity of the measured immigrant-native gap in the job-loss rate to the adjustment for job characteristics in March 2020 suggests that immigrants were more susceptible to job loss because fewer of them were working in "protected" jobs as the various lockdowns and job restrictions were imposed. We explore this implication of the regression results in more detail in the next section. It is important to emphasize, however, that although job characteristics seem to matter, they do not come close to providing a complete explanation for why so many immigrants lost their jobs in the initial labor market shock caused by the Covid-19 pandemic.[7]

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[6] When examining the determinants of job loss between month t and month t+1, the industry and occupation fixed effects are obtained from the survey data reported in month t. As with the other demographic variables, industry and occupation are also interacted with pandemic period fixed effects.

[7] We conducted a comparable regression analysis of the immigrant-native difference in the job-finding rate. The construction of the probability of finding a job requires that a person be out of work in the initial month, precluding the inclusion of occupation and industry fixed effects in the analysis. Prior to the pandemic, immigrant

4. Job Losses and Remote Working

The results presented in Table 3 suggest that job characteristics play an important role in understanding why some groups of workers suffered particularly heavy job losses in the initial phase of the Covid-19 pandemic. In this section, we attempt to identify some of the characteristics of an occupation that may be driving these historic job losses. We also document that immigrant-native differences in those occupational characteristics are partly responsible for the relative increase in the rate of job loss among immigrants.

During the economic slowdown caused by the pandemic, many workers were encouraged or mandated to perform their jobs remotely. Presumably, persons who do the type of work that can be done "off-site" would face a lower risk of job loss. We created an index designed to measure the occupation's "remotability" by using data from the Occupational Information Network (O*NET). Dingel and Neiman (2020) as well as Montenovo et al. (2020) have also used the O*NET data to develop a related "*teleworkable"* measure. Although we use a roughly similar approach, there are several important differences in how we go about constructing the remotability index.

Specifically, we use the *Work Context* and *Work Activities* surveys of O*NET to identify four distinct characteristics of occupations that may measure the ease of remote working: the frequency of telephone conversations on the job, the frequency of using electronic mail, whether the job breaks down information or data into separate parts, and whether the job requires that the

men had a significantly higher (7.5 percentage point) probability of finding a job compared to native men. Native and immigrant women, however, show little evidence of differences in the job-finding rate prior to the pandemic. The regressions reveal a modest increase of about 2 percentage points in the job finding rate for immigrant men relative to native men during the crucial pandemic period, though it should be noted that the coefficients are not precisely estimated. For women, immigrants experienced essentially no change in their job finding rate compared to natives, relative to their pre-pandemic rates.

worker interact with computers (such as programming). We then used principal components to merge the information provided by these four characteristics into a single "remotability index," where a higher value of the index would indicate that the occupation was more remotable (see the Appendix for details on the construction of the index). The occupations that are highly remotable (according to our index) include actuaries and database administrators. The occupations that have a low remotability index include crossing guards and flaggers, or graders and sorters for agricultural products.

Prior to the pandemic, immigrants held jobs that were less suitable for remote work. Table 4 pools the data for the Basic Monthly CPS Files between January 2019 and February 2020 (i.e., prior to the pandemic labor market shock) and estimates a regression model where a worker's index of remotability is the dependent variable. The index is standardized so that it has a mean of zero and a standard deviation of one. Note that immigrant men are far less likely to work in remotable jobs, having a remotability index that is about one-third of a standard deviation below that of native men, while the index for immigrant women is nearly half a standard deviation below that of native women. Adding the demographic controls introduced earlier shrinks (by around half) the remotability index gap between natives and immigrants, though the difference remains large and significant. For illustrative purposes, the table also reports the coefficients of the education fixed effects. These coefficients reveal that more highly educated workers worked in occupations that were much more remotable than workers with less education, with college graduates having a remotability index that was about one standard deviation above the index of workers with less than a high school diploma.

To simplify the graphical exposition, we classify occupations into three categories based on the value of the index: "Low remotability," "Medium remotability," and "High remotability."

The cutoff values of the index were chosen so that the number of workers in each of the three groupings was (roughly) equal. Panel A of Figure 5 shows the fraction of natives and immigrants employed in a high-remotability occupation from January 2019 to June 2021. Consistent with the regression evidence presented in Table 4, both male and female immigrants are much less likely than natives to be employed in high-remotability occupations. Note also that the fraction of workers, both natives and immigrants, employed in a highly remotable occupation increased noticeably between the critical months of March and April 2020, consistent with a much higher rate of job loss for workers in the least remotable occupations. In short, the pre-pandemic occupation distribution of immigrants made them particularly vulnerable to a labor demand shock that had the peculiar characteristic of generating substantial job losses for those employed in jobs that could not be performed remotely.

We document this implication by directly examining the link between the probability that an employed person suffers a job loss and the remotability of the job. Panel B of Figure 5 illustrates the trends in the rates of job loss across the three occupation groups defined above. Prior to the pandemic, low-remotability occupations exhibited only a slightly higher job-loss rate relative to medium- and high- remotability occupations, though it is worth noting that the figure does not control for any worker characteristics such as educational attainment.

In March 2020, the job loss rate spiked across all occupation types, but increased markedly more for workers in low-remotability occupations. In January 2020, for example, the rate of job loss for men employed in occupations with a high degree of remotability was 1.4 percent, while the rate of job loss in the occupations with the lowest degree of remotability was 3.7 percent, a difference of only 2.3 percentage points. In March 2020, the rate of job loss was 19.9 percent for workers in the least remotable jobs and only 6.6 percent for the most remotable jobs, a difference of 13.7 percentage points. Similarly, the rate of job loss among women employed in the least remotable jobs was over 30 percent, as compared to less than 10 percent among women in the most remotable jobs. The visually striking correlation between our index and the rate of job loss suggests that our classification of occupations by the index of remotability captures an important aspect of a worker's ability to do their job outside the traditional work setting.

Table 5 revisits the job loss regressions first reported in Table 3, but with a slight change in specification. We now add the occupation's remotability index to the regression analysis. For expositional convenience, we focus only on the determinants of the difference in the rate of job loss between calendar year 2019 and the dramatic job losses observed between March and April 2020.

The regressions in column 1 (for men) and column 4 (for women) include only calendar month fixed effects, the variable indicating whether the worker is an immigrant, and the interaction between the month fixed effects and the immigration variable, which essentially replicate the results from Table 3. Notably, immigrant men experienced a 5.7 percentage point increase in their job loss relative to natives, compared to their pre-pandemic job loss gap, while immigrant women experienced a 6.5 percentage point increase.

The dependence of the relative rate of job loss of immigrants on the remotability index is addressed in columns 2 and 5, which add regressors giving both the level of the remotability index and an interaction between this index and the March 2020 fixed effect. We have already shown that job-loss rates were larger for workers in less remotable occupations, and that immigrants tend to work in less remotable occupations. Table 5 indicates that, prior to the onset of the pandemic, job remotability had only a mild effect on job loss, with a one-standard-deviation increase in remotability reducing the monthly job-loss rate by around a percentage point for both men and women. But in March 2020, the absolute value of the remotability coefficient increased by 0.048 for men and 0.087 for women. In that month, a one-standard-deviation increase in job remotability reduced job loss by 5.7 percentage points (0.9 + 4.8) for men and 10.0 percentage points (1.3 + 8.7) for women.

Note that adding the variables controlling for job remotability reduces the coefficient of the interaction between immigration status and the March 2020 period fixed effect from 0.057 to 0.041 for men, and from 0.065 to 0.026 for women. Put differently, the difference in the remotability of jobs held by immigrants and natives alone explains about 30 percent of the increase in the job-loss gap between natives and immigrant men, and about 60 percent of the increase for women.

Finally, columns 3 and 6 report the results from a regression specification that adds the vector of demographic variables as well as industry fixed effects (and all of these covariates are interacted with the period fixed effects). The addition of these controls does little to change the immigrant-native relative gap in job-loss rates in March 2020 (and, for women, it actually increases the magnitude to 0.039). The regression analysis, therefore, suggests that differences in the index of job remotability between immigrants and natives played a unique and crucial role in creating the very large job losses experience by the immigrant population at the time.[8]

We can visually illustrate the strong connection between occupational remotability and job losses by defining an occupation as the unit of analysis. We divide our monthly CPS sample into two periods: the early pandemic period (April-June 2020), and a pre-pandemic baseline

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[8] We also used the Gelbach (2016) method of decomposing changes in coefficients attributable to individual covariate groups. This decomposition analysis confirms that the index of remotability is by far the most significant covariate in explaining the increase in the immigrant-native gap in the job-loss rate at the beginning of the pandemic.

period of the same calendar months (to account for potential seasonal variations) but a year prior (April-June 2019). For each period, we calculate the fraction of the total working-age population working in occupation *j* (and we pool men and women to reduce the sampling error introduced by small sample sizes in the cells). We then calculate the change in this fraction between the two periods in each occupation as follows:

$$\Delta Z_j = \frac{E_{j1}}{P_1} - \frac{E_{j0}}{P_0}, \tag{4}$$

where P_t is the total population aged 21-64 in period t, with $t = 0$ is the pre-pandemic period and $t = 1$ is the early pandemic period; and E_{jt} is the total employment in occupation j in period t.

Given the large reduction in employment in the early pandemic, we would expect that the change in the fraction employed in each occupation will be negative overall. We are interested, however, in exploring how ΔZ_j is related to the index of remotability. Figure 6 shows the scatter diagram relating the change in percent employed in each occupation to the remotability index.[9] There is a clear, positive relationship between the index and the change in the fraction of the population employed in that occupation. We also plot the regression line, weighted by employment in each occupation. As expected, occupations that are more remotable experienced, on average, either a smaller reduction in employment or in some cases, greater employment growth.

Finally, to illustrate the relationship between the clustering of immigrant workers in particular occupations, job losses, and the index of remotability, we rank occupations by the

[9] Our sample includes only occupations with at least 50 workers in both periods, which gives us 282 occupations.

immigrant share of workers in that occupation and divide occupations into one of three groups: low-immigrant occupations are those in the bottom quintile of the distribution; medium-immigrant occupations are those in the middle three quintiles; and high-immigrant occupations are those in the highest quintile. Figure 6 also reveals that the medium-immigrant occupations are well-spread throughout the distribution of the remotability index. Nevertheless, there is an obvious clustering of occupations with relatively few immigrant workers among those that have higher remotability indices (where relatively little employment change occurred), while occupations with relatively many immigrant workers tend to be among the occupations with the lowest remotability index (where employment tended to fall).

5. Undocumented Status and Employment Trends

The regression results reported in the previous sections ignored the distinction between legal and undocumented immigrants, even though a large fraction of the immigrant population is undocumented and undocumented immigrants may have been affected differentially by the Covid-19 labor market shock. According to the latest estimates from the Department of Homeland Security (Baker, 2019), there were 12.0 million undocumented immigrants in the United States in January 2015, accounting for about 27.8 percent of the foreign-born population. The immigration status of a foreign-born person is likely to affect labor market opportunities, and that impact may be particularly severe during extreme economic downturns.

Although the Basic Monthly CPS does not contain a variable indicating whether a particular foreign-born person is undocumented, a number of recent papers employ imputation methods to assign every foreign-born person in the sample an “immigration status” code. These imputation methods have been used to study labor supply differences between legal and undocumented immigrants (Borjas, 2017), the impact of the Deferred Action for Childhood Arrivals (DACA) executive action on the education of immigrant children (Hsin and Ortega, 2018) and on labor market outcomes (Amuedo-Dorantes and Antman, 2017), and the wage penalty to undocumented immigration (Borjas and Cassidy, 2019).

It is of interest to determine if the historic disruptions resulting from the pandemic had a different deleterious effect on undocumented immigrants because their employment contract is more tenuous, or because the kinds of jobs typically held by undocumented workers "protected" them from the economic consequences. As is common in much of this literature, we build on the work of Passel and Cohn (2014) to construct an "immigration status" indicator for a subset of the foreign-born persons sampled in the January 2020-June 2021 Basic CPS files.

In rough terms, the Passel-Cohn algorithm identifies the foreign-born persons in a particular sample who are likely to be legal, and then classifies the residual group of foreign-born persons as likely to be undocumented. The residual method used in our analysis classifies a foreign-born person as a *legal* immigrant if any of the following conditions hold:

a. that person arrived before 1980;
b. that person is a citizen;
c. that person receives Social Security benefits, SSI, Medicaid, Medicare, or Military Insurance;
d. that person is a veteran, or is currently in the Armed Forces;
e. that person works in the government sector;
f. that person resides in public housing or receives rental subsidies, or that person is a spouse of someone who resides in public housing or receives rental subsidies;
g. that person was born in Cuba (as practically all Cuban immigrants were granted refugee status);
h. that person's occupation requires some form of licensing (such as physicians, registered nurses, air traffic controllers, and lawyers);
i. that person's spouse is a legal immigrant or citizen.

We use this algorithm to construct an undocumented status identifier in the March 2019 and March 2020 ASEC files (see Borjas, 2017 for further details). It is not possible to apply the algorithm directly to the CPS Basic Monthly files because many of the variables required to impute undocumented status (such as receipt of various types of benefits) are not available in the Basic Monthly files.

After imputing the immigration status of each foreign-born person in the CPS ASEC files of 2019 and 2020, we then used the IPUMS-created identifier for a particular person in the CPS sample (*cpsidp*) to match the subsample of persons who appear in any of the ASEC files and in at least one of the Basic Monthly files during our sample period of January 2019 through June 2021. The sample produced by this matching exercise has two key characteristics. First, because of the sampling strategy used by the CPS, a person who appears in the March ASEC of any given year must also appear in the corresponding March Basic Monthly file as part of the basic rotation. This implies that a person who appears, say, in the March 2020 ASEC file is in the 1st to 4th month of the initial rotation or in the 5th to 8th months of the second (and final) rotation. As a result, no one sampled in the Basic files between July and November 2020 could have appeared in the March 2020 ASEC. The sampling rotation used by the CPS, therefore, makes it impossible to construct a continuous trend in employment rates by legal status throughout the entire 2019-2021 period.

The second (related) property of the matched sample is that it contains fewer observations than the original CPS. For example, the March 2019 and March 2020 ASEC files allows us to match only 36,924 persons (out of a potential 53,087 observations) in the April 2020 Basic file. The issue is more problematic for the data summarizing employment conditions in Spring 2021. In order to track the employment of specific persons during the Covid pandemic, we can only use those persons who were sampled in March 2020 in the initial rotation and are in their second rotation during the months of March-April 2021.[10]

It is evident that measurement error enters the exercise at various stages, including the construction of the Pew imputation algorithm itself, the restriction that we can only identify the undocumented status of persons who appear both in one of the ASEC files *and* in the Basic Monthly files, and the fact that the construction of the person-level identifier in the IPUMS-CPS (*cpsidp*) does not perfectly match the same person across different CPS cross-sections.[11] Nevertheless, this exercise provides the only (admittedly rough) information that can be gathered from available data about how the pandemic affected the employment opportunities of undocumented immigrants.[12]

Figure 7 shows the trends in the employment rate of natives, legal immigrants, and undocumented immigrants (by gender) during the sample period. As noted above, due to the rotational structure of the CPS, none of the respondents interviewed between July and November in any year are ever administered the March ASEC questionnaire and can be assigned an imputed legal status (the break in the trend is indicated with dashed lines in the figure). Consistent with Borjas (2017), male undocumented immigrants exhibited higher employment

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[10] Restricting the 2021 sample to persons who were also observed in 2020 helps mitigate issues related to how the CPS survey sample responses changed due to the COVID-19 pandemic; see Rothbaum and Bee (2021).

[11] Note that our algorithm implies that the immigration status of a person may change from one CPS-ASEC file to another for two distinct reasons. First, the person-level identifier in the IPUMS data may be incorrectly assigned to different people. Second, the immigration status of a specific person might have changed from one year to the next (e.g., an undocumented person married a U.S. citizen, thereby becoming a legal immigrant). The number of cases where we observe such changes in immigration status is relatively small. Our data indicate that 92 (79) percent of persons initially classified as legal (undocumented) immigrants in year *t* are again classified as legal (undocumented) immigrants in year *t*+1, See Drew, Flood, and Warren (2014) for a detailed discussion of the measurement error introduced when matching specific persons across CPS cross-sections (regardless of immigration status).

[12] Even though we do not need to assign the legal status of natives, we mitigate any selection effects that might exist in the subsample of persons who can be successfully matched in the ASEC and Basic files by restricting the analysis to the subsample of native persons who can also be matched between the two data sources.

rates than legal immigrants prior to the pandemic, who in turn had higher employment rates than natives. For women, the reverse holds, with native women having the highest employment rates, followed by legal immigrants and finally undocumented immigrants with the lowest employment rates.

Not surprisingly, there is a dramatic drop in employment rates in April 2020 for all groups (natives, legal immigrants, and undocumented immigrants). Between January and April 2020, the male employment rate dropped from 81 percent to 73 percent for natives, from 87 percent to 73 percent for legal immigrants, and from 90 percent to 76 percent for undocumented immigrants. For women, the respective statistics are 73 percent to 63 percent for natives, 64 percent to 52 percent for legal immigrants, and 55 percent to 41 percent for undocumented immigrants. The figure also shows a much faster employment recovery for undocumented immigrant men (which will be discussed in greater detail below).

Figure 8 illustrates the job-loss rates for natives, legal immigrants, and undocumented immigrants for the crucial months between December 2019 to May 2020. For men, all three groups (natives, legal immigrants, and undocumented immigrants) exhibited nearly identical job-loss rates prior to the pandemic. However, between January and March 2020, the job loss rate of both legal and undocumented immigrants increased by essentially the same amount (15.0 percentage points for legal immigrants and 16.1 percentage points for undocumented immigrants), while the change was only 9.7 percentage points for natives. For women, undocumented immigrants faced higher job loss rates than legal immigrants prior to the pandemic, who in turn faced higher job-loss rates than natives. Between January and March 2020, all three groups experienced significant increases in the job-loss rate: 12.7 percentage points for natives, 17.2 percentage points for legal immigrants, and 23.4 percentage points for undocumented immigrants. Strikingly, nearly a third (30.3 percent) of the undocumented women who were employed in March 2020 had lost their jobs by April 2020.

The results from Figure 8 show that legal and undocumented men experienced a similar increase in job-loss rates when the repercussions of the pandemic first hit the labor market, while undocumented immigrant women experienced a greater increase in job loss than legal immigrant women. As we showed earlier, a significant fraction of the relative increase in job-loss rates experienced by immigrants can be explained by job characteristics, and particularly the extent to which the jobs were remotable. We now conduct a similar regression analysis to that reported in Table 5, but divide the immigrant populations into legal and undocumented workers. As in Table 5, we use two time periods: pre-pandemic (i.e., January-December 2019) and pandemic (March 2020).

The key regression coefficients are reported in Table 6. The baseline regressions (columns 1 and 4) include controls for only month fixed effects, period effects, and period effects interacted with immigration status. In March 2020, the job-loss rates of legal and undocumented immigrant men increased by nearly identical amounts, 5.6 and 5.8 percentage points, respectively, relative to native men. For women, however, immigration status appears to be far more relevant, with legal immigrants experiencing a 4.9 percentage point increase in job loss relative to native women, whereas undocumented women experienced a substantially larger increase of 12.1 percentage points in job loss relative to native women.

Columns 2 and 5 add the variables controlling for differences in the remotability index. As suggested by Table 5, the immigrant-native differences in remotability help explain the spike in immigrant job loss in March 2020 for both legal and undocumented immigrants. Note, however, that the index explains a modest portion of the legal immigrant job loss relative to native men, reducing the interaction coefficient from 0.056 to 0.048, while for undocumented immigrants, remotability explains more than half of the increase in job loss, reducing the coefficient from 0.058 to 0.023. For women, remotability plays an important role in explaining the job loss increase for both native and undocumented women.[13] Adding controls for demographics and industry fixed effects (columns 3 and 6) does little to help explain the job loss increase for legal and undocumented immigrants, and for all but undocumented men, actually increases the magnitude of the March 2020 coefficient.

6. Unemployment Insurance and the Employment Recovery

As noted earlier, the decline in the employment rate of natives and the steeper decline in the employment rate of immigrants (due to their exceptionally high job-loss rates between March and April 2020) was followed by a year-long recovery for both groups. The employment rate of native men, which had fallen from 81.0 to 72.3 percent between February and April 2020, had risen back to 78.4 percent in June 2021. Similarly, the employment rate of immigrant men, which suffered a much steeper drop between February and April 2020 (from 88.7 to 72.8 percent), rose even faster in the subsequent year, and stood at 84.9 percent in June 2021. By 2021, the immigrant-native employment gap had roughly returned to its pre-pandemic "equilibrium."

We now examine the determinants of the immigrant-native gap in the rate of employment recovery, with a special emphasis on how the recovery was influenced by the generous unemployment insurance (UI) benefits made available to unemployed workers during the

[13] The full regression specification, which adds regressors for the demographic variables and industry fixed effects, is shown in columns 3 and 6 of Table 6. These additional controls do not significantly affect the crucial March 2020 interaction coefficients for legal or undocumented men. For women, however, the introduction of the additional regressors actually increases the magnitude of the interaction coefficients.

pandemic. It is well known (Ganong, Noel, and Vavra, 2020) that the federally funded UI supplements offered during the pandemic months led to record-high levels of the replacement ratio (i.e., the fraction of lost weekly earnings that are replaced by UI benefits).

Our empirical analysis of the link between UI and the rate of employment recovery will exploit the observed difference in the employment recovery rate between natives, legal immigrants, and undocumented immigrants. The breakdown of the immigrant population by legal status is particularly relevant in this context because undocumented immigrants, unlike natives and legal immigrants, do not qualify for the federally funded UI benefit supplements.[14] As a result, the employment trends observed among undocumented immigrants provide a "benchmark" of what might have been observed in the absence of the generous UI benefits provided to unemployed workers during the pandemic.

To easily summarize the empirical evidence (and to increase the sample size of undocumented workers), the empirical analysis of the employment recovery reported below focuses on the change in employment rates observed between the pooled months of April-May 2020 (when the initial demand shock of the Covid pandemic reduced the employment rates of both immigrants and natives to their lowest point) and the Spring 2021 period (defined as the pooled months of March, April, and May 2021). Beginning in May 2021, the concern that employers could not attract workers because of the availability of generous UI supplements led

[14] A small number of states and localities offered partial benefits to unemployed undocumented immigrants, including the states of California and Oregon, and the cities of Austin, Texas and Tucson, Arizona (Suro and Findling, 2021). We ignore these targeted programs in what follows as the programs covered only a small part of the undocumented population and offered far less generous assistance than that available to natives or legal immigrants. For instance, the California Disaster Relief Assistance for Immigrants program established a fund of only $125 million "to benefit 150,000 undocumented workers" with "recipients…receiving direct one-time payments."

some states to consider curtailing some of those benefits. As a result of these initiatives, 25 states suspended a \$300 federally funded weekly UI supplement in June 2021 (Henney, 2021).

We use a pooled sample of the monthly CPS Basic files for April-May 2020 and Spring 2021 to estimate a regression model designed to measure the difference in the adjusted recovery rate between immigrants and natives. Consider the regression:

$$y_{it} = \alpha_0 M + \alpha_1 t + \alpha_2 (M \times t) + \beta X_{it} + \epsilon \tag{5}$$

where *M* is an indicator variable set to unity if person *i* is an immigrant; *t* is an indicator variable set to unity if the observation is drawn from the pooled Spring 2021 Basic CPS; and *X* is the vector of socioeconomic characteristics introduced earlier). The regression in equation (5) is estimated separately by gender.

The first two columns of Panel A of Table 7 summarize the basic results for men. The regression reported in column 1 does not include any regressors in the vector *X*, so that the coefficients simply summarize the trends in the raw data between April-May 2020 and Spring 2021. There was a very strong recovery in employment rates for natives—the coefficient of the period effect (α_1) is 0.054 (0.005). The regression also shows that the employment recovery was about twice as strong for immigrants. The coefficient of the interaction between the immigration status variable and the time fixed effect is 0.057 (0.013).

The second column of the table shows that these point estimates of the recovery rates do not change appreciably when the regression includes a full set of other explanatory variables to adjust for differences in observable characteristics between immigrants and natives. The adjusted employment rate of native men grew by 5.4 percentage points between the low reached in April-

May 2020 and Spring 2021, and the immigrant-native gap in the employment recovery rate was 5.1 percentage points, so that immigrant men experienced a 10.5 (or 5.4 + 5.1) percentage point increase in employment during this time.

Columns 3 and 4 reproduce the regression analysis for native and immigrant women. Note that that the employment rate of native women grew by slightly more than the growth exhibited by native men. In the regression that controls for all demographic characteristics, for example, the adjusted employment rate of native men grew by 5.4 percentage points between April-May 2020 and Spring 2021, while the adjusted employment rate of native women grew by 7.1 percentage points. Note also, however, that although the employment recovery rate was about twice as high for immigrant men as for native men, the female regressions show that the immigrant-native gap in recovery rates was far smaller (3.1 percentage point gap for women, versus 5.1 percentage point gap for men).

There has been extensive discussion about the extent to which the employment recovery between 2020 and 2021 was hampered by the presence of generous UI benefits granted to workers put out of work by the various lockdowns and workplace restrictions that were enacted at the beginning of the pandemic (Antoni and Mulligan, 2021). As noted above, undocumented workers do not qualify for such benefits. This fact suggests that the differences in the employment trends of natives, legal immigrants, and undocumented immigrants during the recovery period between Spring 2020 and Spring 2021 may provide valuable information about the role played by the high levels of UI benefits in determining the speed of recovery.

Figure 7 illustrated the trends in the employment rate for the three groups between January 2020 and April 2021. The raw data clearly show that undocumented immigrant men had a faster recovery rate than either natives or legal immigrants (with the gap between undocumented immigrants and natives being particularly large) between the early months of the pandemic and early 2021. The bottom panel of Table 7 reports the regression coefficients comparable to those reported in the top panel except that we now allow for three groups in the comparison: natives (the baseline), legal immigrants, and undocumented immigrants. The "excess" recovery rate of undocumented immigrants (relative to natives) is numerically large and statistically significant, even after adjusting for differences in demographic characteristics. In particular, the recovery rate of undocumented immigrants was 7.2 percentage points larger than that of natives, while the recovery rate of legal immigrants was "only" 4.8 percentage points larger than that of natives. Note, however, that the standard errors are sufficiently high that we cannot reject the hypothesis that the recovery rates for legal and undocumented immigrants are the same.

As noted earlier, because the undocumented immigrant population did not qualify for the federally funded UI benefits made available during the Covid pandemic, this population can serve as a control group that describes what the employment path would have been in the absence of such benefits for groups that did qualify (i.e., natives and legal immigrants). We examine the link between the rate of employment recovery, undocumented immigration, and unemployment insurance by exploiting interstate variation in the relative level of UI benefits. Consider the following regression model:

$$\begin{aligned} y_{ijrt} = \sum_{j} \left[\alpha_{1j}\left(D_{ij} \times t\right) + \alpha_{2j}\left(D_{ij} \times t \times B_r\right)\right] \\ + \theta_{rj} + \beta_0 F_{it} + \beta_1 X_{it} + \beta(X_{it} \times F_{it}) + \epsilon, \end{aligned} \tag{6}$$

where y_{ijrt} gives the employment status of individual i in nativity group j (i.e., native, legal immigrant, or undocumented immigrant), in state r, at time t. The regression model in (6) includes a vector of interacted fixed effects θ_{rj} between state and nativity groups. These fixed effects net out any state-specific differences across natives, legal immigrants, and undocumented immigrants that are constant over time. They also net out time-invariant differences across the three groups, as well as time-invariant differences across states.

The crucial set of regressors in equation (6) appears under the summation sign. For each nativity group j, the regression includes two variables: an interaction between a group indicator variable D_{ij} set to unity if person i is a member of group j and the variable t indicating if the observation is drawn from the 2021 pooled CPS; and a three-way interaction between the group indicator variable, the calendar year 2021 fixed effect, and a variable measuring the level of unemployment benefits in the state, B_r. Our measure of B_r is given by the ratio of the (maximum) weekly benefits offered by the state in April 2021 (just prior to the time when about half the states moved to discontinue the $300 weekly federally funded UI supplement) to the average weekly wage in the state.[15]

The specification in (6) implies that the coefficient α_{1j} measures the recovery rate for type-j workers in a state where the replacement ratio equals zero. Of course, this is a linear extrapolation at an extreme value of the replacement ratio that is never observed in the data, as the actual range of the UI replacement ratio is from 0.42 to 0.82. Note that the coefficient α_{2j} measures how the interstate variation in the recovery rate of type-j workers is related to interstate differences in the replacement ratio. The hypothesis that UI benefits have no employment

[15] The average weekly wage is calculated in the 2020 ASEC CPS using the sample of all workers aged 21-64.

disincentive effects on any workers implies that the vector of coefficients α_2 should be exactly equal to zero.

Finally, because the analysis will be identifying the employment effects of UI benefits by exploiting interstate variation in the recovery rate for a specific group j, the sample size for many (j, r, t) cells will be very small, potentially introducing sizable sampling error. We minimize this problem by pooling all men and women in this specific context, and interacting the vector of demographic variables X with a variable F_{it} that indicates the gender of person i.

The estimation of equation (6) yields the following results for the two coefficients of interest, α_{1j} and α_{2j}, which define how the predicted employment recovery between 2020 and 2021 differs between natives, legal immigrants, and undocumented immigrants:

Natives:
$$\underset{(0.023)}{y = 0.135\, t} - \underset{(0.039)}{0.125\, (t \times B_r)} \tag{7a}$$

Legal Immigrants:
$$\underset{(0.068)}{y = 0.216\, t} - \underset{(0.117)}{0.216\, (t \times B_r)} \tag{7b}$$

Undocumented Immigrants:
$$\underset{(0.116)}{y = 0.054\, t} + \underset{(0.194)}{0.138\, (t \times B_r)} \tag{7c}$$

The regressions coefficients summarized in equations (7*a*) - (7*c*) unambiguously indicate that higher levels of the UI replacement ratio slowed the recovery rate experienced by the UI-eligible population (i.e., natives and legal immigrants) and had little impact on the recovery rate of undocumented immigrants, where the relevant coefficient is statistically insignificant. In fact, the data suggest that, if anything, there is a slight positive correlation between the recovery rate of undocumented immigrants and the replacement ratio.[16]

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[16] If our imputation algorithm correctly identified a random sample of undocumented immigrants *and* if the level of UI benefits in the state is uncorrelated with underlying economic conditions, the coefficient of the interaction term in equation (7*c*) between the 2021 fixed effect and the replacement ratio should be exactly equal to

Table 8 uses these coefficients to carry out a prediction exercise that allows us to evaluate the quantitative importance of UI benefits in slowing down the rate of employment recovery of the eligible groups. Note that the actual recovery rate (i.e., the growth in the employment rates between Spring 2020 and Spring 2021) varies substantially across the three groups. It was 6.3 percentage points for natives, 9.2 percentage points for legal immigrants, and 13.9 percentage points for undocumented immigrants. We use the regression coefficients to predict the recovery rate for group *j* if the replacement ratio was set at its lowest observed value (Arizona, with a replacement ratio of .45). Table 8 shows that, at this minimum level of the replacement ratio, the differences in the recovery rate across groups is far smaller than what was actually observed. The predicted recovery rate of natives is 8.1 percentage points and the predicted recovery rate of undocumented immigrants is 11.1 percentage points. The 3-percentage point difference in predicted recovery rates points is far below the actual 8-percentage point difference. In other words, at the lowest observed value of the replacement ratio, the recovery rate of native workers would not have been that much lower than that of undocumented immigrants.

The table also predicts the recovery rates at the mean value of the replacement ratio (which is 0.62). The predicted recovery rate of natives in the mean state is 6.3 percentage points, while the predicted recovery rate of undocumented immigrants in the mean state is 13.4 percentage points, a difference of about 7 percentage points, nearly the same as the actual rate of 8 percentage points. In short, the different responses to the availability of generous UI benefits

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zero. A positive coefficient would suggest that the level of UI benefits across states is not randomly determined, but instead happens to be larger in states where the underlying economic and political fundamentals would have produced a much more rapid employment recovery regardless. If such a spurious correlation were statistically significant (*and* if the spurious correlation affected all nativity groups equally), the causal impact of UI benefits on the employment recovery of natives could be obtained by differencing the regressions in (7*a*) and (7*c*)—effectively identifying the impact of UI on native employment net of the spurious correlation isolated by the regression in the undocumented sample.

by natives and undocumented immigrants accounts for almost all of the difference in the actual recovery rates between the two groups.[17]

Finally, it is instructive to illustrate graphically the interstate relation between the recovery rate and the replacement ratio, and how this relation varies among the nativity groups. We first calculate the adjusted employment rate for the cell defined by group *j* in state *r* at time *t*. The adjusted employment rate for cell (*j, r, t)* is obtained by estimating the regression:

$$y_{ijrt} = \theta_{jrt} + \beta_0 F_{it} + \beta_1 X_{it} + \beta (X_{it} \times F_{it}) + \epsilon, \tag{8}$$

where the estimate of the fixed effect θ_{jrt} gives the adjusted employment rate for the cell. We estimate the adjusted employment rate in equation (8) using the pooled samples of the April-May 2020 Basic CPS files and the Spring 2021 (March-April-May) files.

We define the recovery rate for group *j* in state *r* by differencing the fixed effects from equation (8):

$$R_{jr} = \theta_{jr,2021} - \theta_{jr,2020} \tag{9}$$

In short, the variable R_{jr} gives the (adjusted) growth in the employment rate between the period immediately after the pandemic shock hit the U.S. labor market and Spring 2021 for cell (*j, r*).

[17] Our results are not sensitive to the definition of the level of UI benefits. We replicated the analysis using a Department of Labor (DOL) measure of the mean replacement ratio in the state that uses a small sample of UI benefit recipients to calculate the statistic (U.S. Department of Labor, 2021). The correlation between the DOL measure of the replacement ratio for the first quarter of calendar year 2021 and our measure is 0.76, so it is not surprising that the results produced by using this alternative measure are qualitatively similar to those reported in the text.

Figure 9 illustrates the data for native workers, legal immigrant workers, and undocumented workers.[18] Consider initially the results for natives in the top panel of the figure. It is evident that there is a negative correlation between the rate at which the (adjusted) employment rate of natives grew between 2020 and 2021 and our measure of the generosity of the UI benefits offered by the state of residence. The middle panel of the figure illustrates the relation between the recovery rate of legal immigrant men and the replacement ratio. This scatter diagram also reveals a negative correlation between the two variables. Finally, the bottom panel shows the relation between the recovery rate of undocumented immigrants and the replacement ratio. There is, if anything, a slight positive correlation between the recovery rate and the replacement ratio for this ineligible group.

7. Summary

Immigrants now make up nearly a fifth of the U.S. workforce. Immigrant men have historically had higher employment rates than native men, while immigrant women have had lower employment rates than native women. The historic Covid-19 labor market shock, which led to unprecedented job losses, differentially affected the employment opportunities of immigrant and native workers both at the outset of the pandemic and during the subsequent recovery.

Prior to the pandemic, the employment rate of immigrant men was about 6 percentage points higher than that of native men. In contrast, the employment rate of immigrant women was about 9 percentage points lower than that of native women. Our analysis uses data from the CPS

[18] It is worth noting that the intercept and slopes of the regression lines drawn in the figures exactly replicate the coefficients of the two- and three-way interactions in equations (7a) – (7c).

Basic Monthly files to document the differential impact of the pandemic on immigrant and native employment opportunities. The initial adverse employment effect in March-April 2020, as the various lockdowns and work restrictions went into effect, was much larger for foreign-born workers. The employment advantage that immigrant men had enjoyed prior to the pandemic disappeared. By April 2020, both groups had essentially the same employment rate.

The subsequent economic recovery (through June 2021) also affected immigrants and natives differentially. Specifically, the employment rate of immigrant men increased at a much faster rate than that of native men in this period. By June 2021, the pre-pandemic employment advantage of immigrant men had been reestablished.

Our analysis examines the determinants of both the initially larger job losses suffered by immigrants at the outset of the pandemic and of the subsequent larger employment gains in the recovery period. Part of the relatively larger adverse effect that the pandemic initially had on immigrant employment can be traced to the fact that immigrants and natives tend to do different jobs. Immigrants were less likely to be employed in jobs that could be done remotely prior to the pandemic, and were much more likely to lose their jobs as the work restrictions only allowed workers with "remotable" skills to work from home.

Our analysis of the employment recovery focuses on the potentially different role played by unemployment insurance benefits for a relatively large subsample of the immigrant population. The employment rate of undocumented immigrants increased at a much faster rate during the recovery period than the employment rates of either natives or legal immigrants. Undocumented immigrants, however, were not eligible for the UI benefits offered to unemployed workers during the pandemic. This allows us to exploit interstate differences in UI benefits, as well as differences in labor supply decisions between eligible and non-eligible unemployed workers, to identify the causal impact of unemployment insurance on the employment recovery. The evidence suggests that the disincentive effects of the UI benefits are quite large, accounting for much of the difference in the employment recovery rates of natives and undocumented immigrants.

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Appendix: Construction of an index measuring the ease of remote working

This appendix describes the procedure used to arrive at our index that measures the difficulty of working remotely. We make use of two O*NET surveys: Work Context and Work Activities. The Work Context survey provides data on the frequency that a worker uses the telephone or email (never, once a year, once a month, once a week, or daily). For each attribute, we use the weighted average score, where never = 1 and daily = 5. Hence, each Work Context attribute in the O*NET has a score from 1 to 5. The attributes in the Work Activities survey include, for example, the analysis of data or information. We use the importance (as opposed to level) of each attribute which, like the work context attributes, is scored from 1 (low) to 5 (high). Thus, from the O*NET, for each occupation we have a measure of each attribute's importance ranging from 1 to 5.

Assigning the O*NET tasks to the CPS requires several steps, due to differences in occupational coding schemes. The O*NET uses Standard Occupational Classification (SOC) codes, whereas the CPS uses Census occupation codes.

We proceed in two steps. We first use the 2015-2019 five-year pooled ACS, which include occupation coded using both the Census codes and the SOC codes, and merge the ACS data with the occupational attributes from the O*NET, using the SOC codes. Unfortunately, for some workers, the Census masks up to four of the final digits of the occupation. For example, occupation 514XXX includes occupations 514035, 514081, 514192, 514199, and refers to miscellaneous metal plastic workers. A worker in the ACS who is actually in occupation 514035 would, therefore, show up with the occupation code 514XXX. We address this issue by aggregating occupations, taking the average across the occupations of each attribute from the O*NET, and repeating this process at four levels of aggregation. So, for example, to match workers coded in the ACS with an SOC occupation 514XXX, we aggregate up three levels to 514, where the O*NET attributes for this aggregated occupation code are calculated by averaging across all occupations that begin with 514. When merging the O*NET with the ACS, we prioritize the highest level of granularity possible; for example, occupation 514194 has no masked digits, and so is merged with the O*NET at the full six-digit level. For occupations not matched at the six-digit level, we try to match at the five-digit level, then at the four-digit level, etc., until all workers are matched.

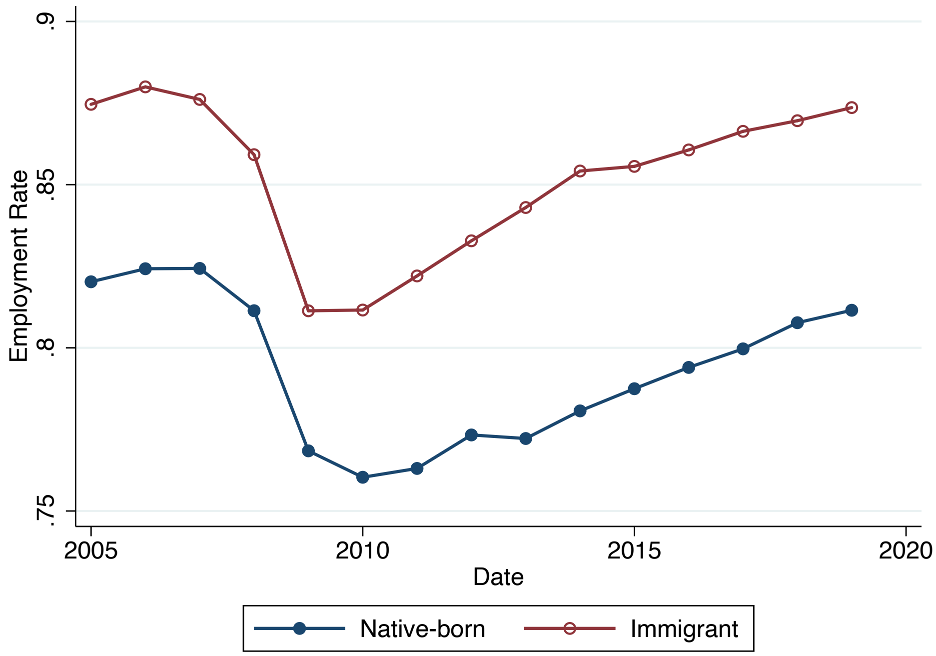
This procedure yields an ACS data file where each worker has been assigned their occupation attributes from the O*NET. We then take the average of each attribute by the IPUMS-provided and harmonized *occ2010* occupation code. We keep a single observation for each *occ2010* occupation code. Since the IPUMS CPS also contains the *occ2010 code,* we are now able to merge occupational attributes with individuals in the CPS.

Our goal is to use the occupational attributes from the O*NET to develop a measure that captures the ease with which a worker in an occupation can work remotely. While the O*NET includes a rich set of occupational attributes, we want to simplify our analysis by grouping occupations into the opportunities for remote work. We use four measures that we believe would reasonably be positively related to the opportunities for remote working: Telephone (4.C.1.a.2.f), Electronic Mail (4.C.1.a.2.h), Analyzing Data or Information (4.A.2.a.4), and Interacting with Computers (4.A.3.b.1).

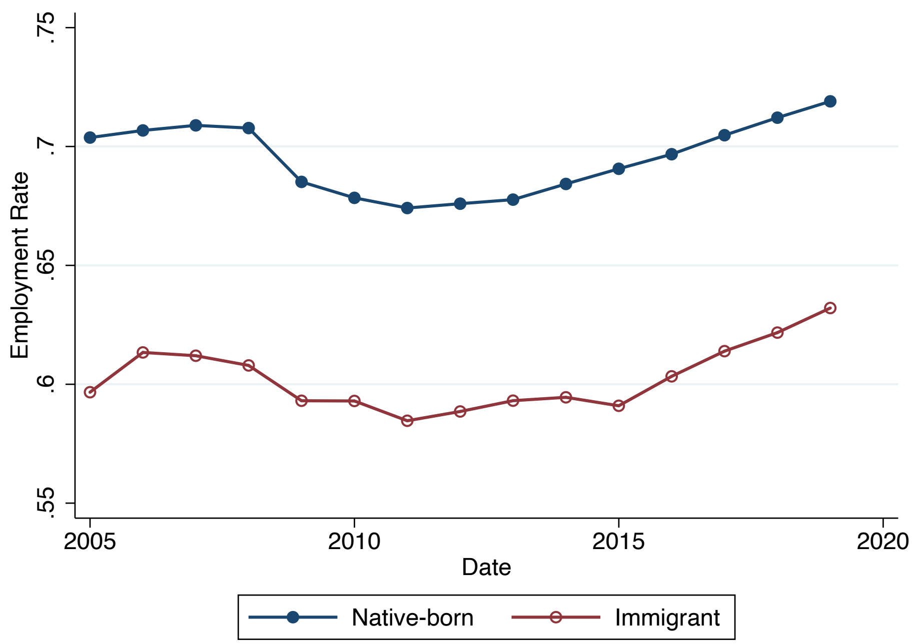
We reduce these four attributes to a single measure using principal component analysis and extracting the first component, which is commonly used in the occupational task literature (e.g., Yamaguchi 2012, Cassidy 2019). This yields a single index that (presumably) measures remote workability. The index is standardized to have a mean of zero, and a standard deviation of one in the 2019-2020 Basic Monthly CPS.

Figure 1. Employment rate in Basic Monthly CPS, 2005-2019

A. Men



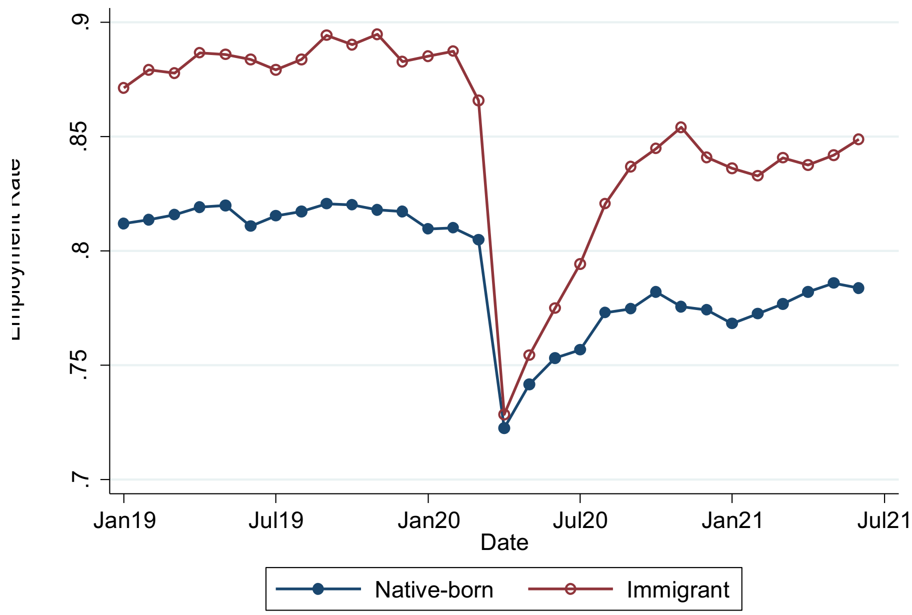
B. Women



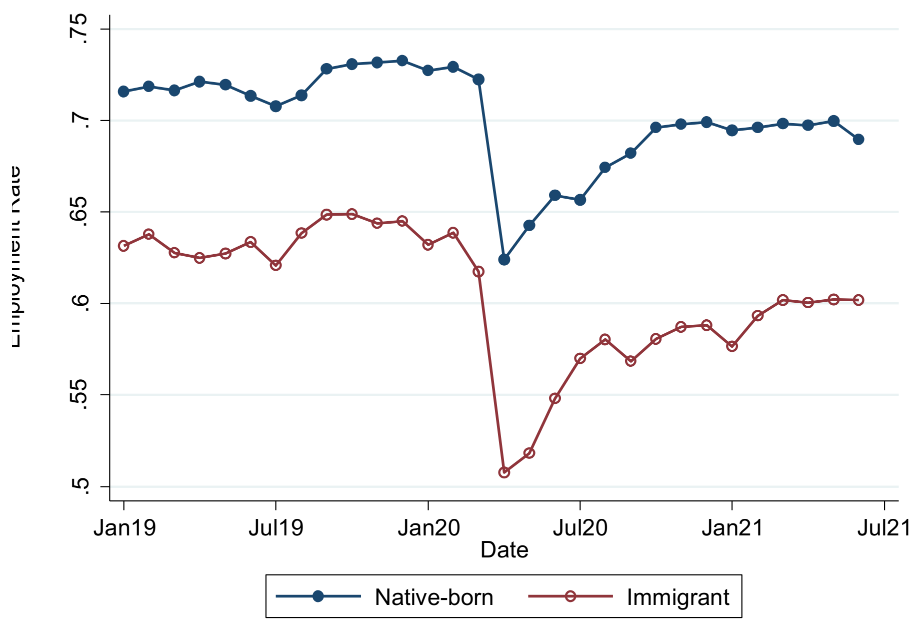
Notes: Figure shows the seasonally adjusted employment rate per month. All samples consist of persons aged 21-64 who are not enrolled in school. The employment rate gives the fraction of persons who are "at work" or "has job, not at work last week."

Figure 2. Employment rate in Basic Monthly CPS, January 2019-June 2021

A. Men



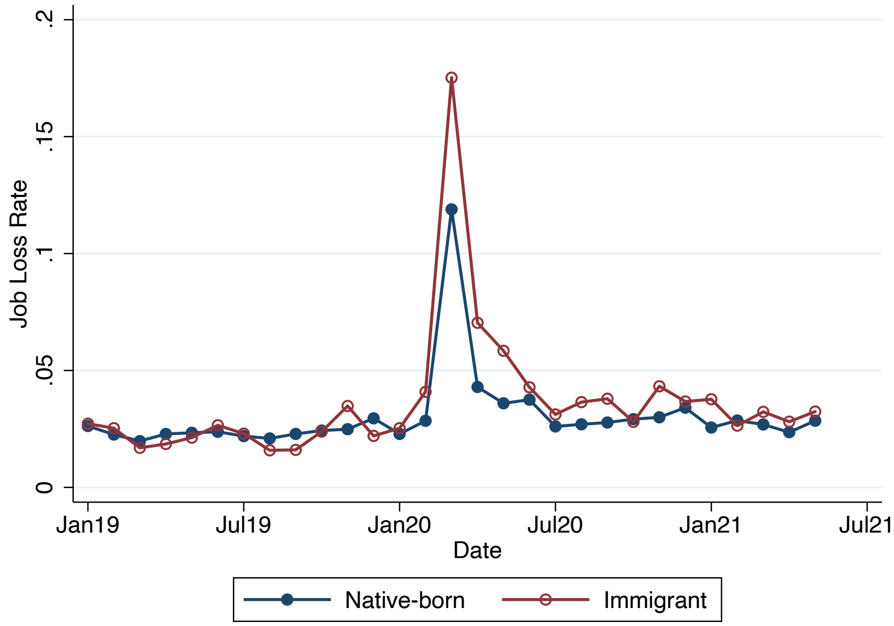
B. Women



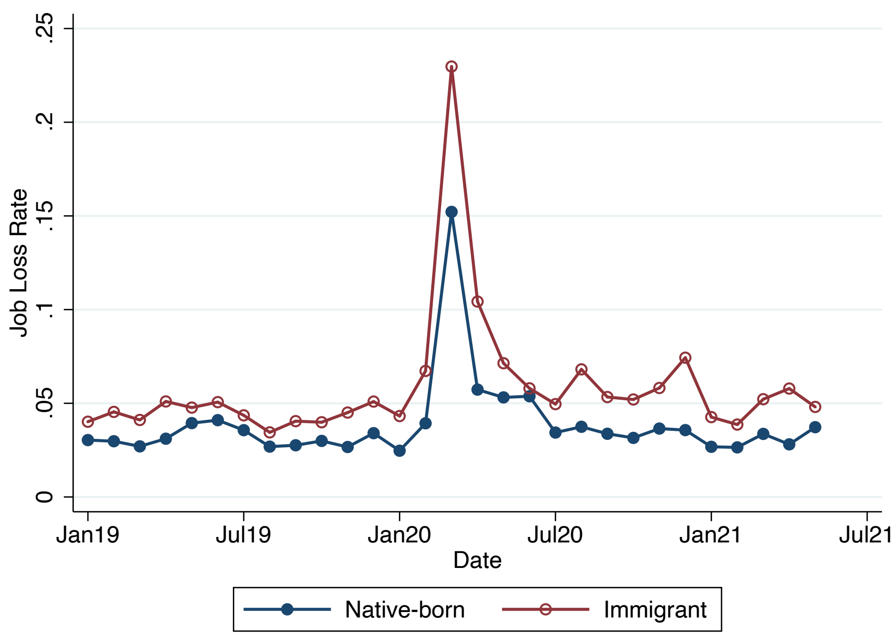
Notes: All samples consist of persons aged 21-64 who are not enrolled in school. The employment rate gives the fraction of persons who are “at work” or “has job, not at work last week.”

Figure 3. The job-loss rate, matched Basic Monthly CPS, January 2019-June 2021

A. Men



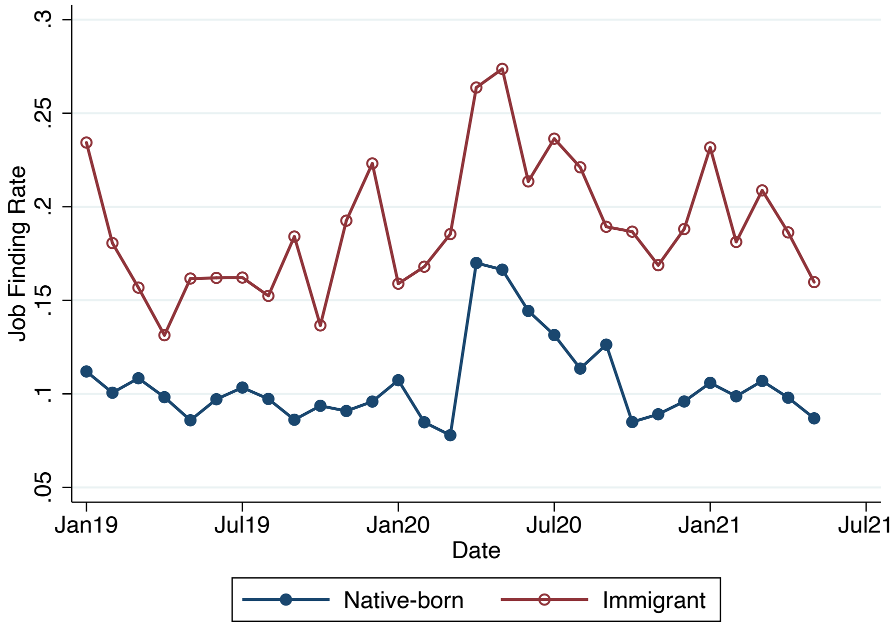
B. Women



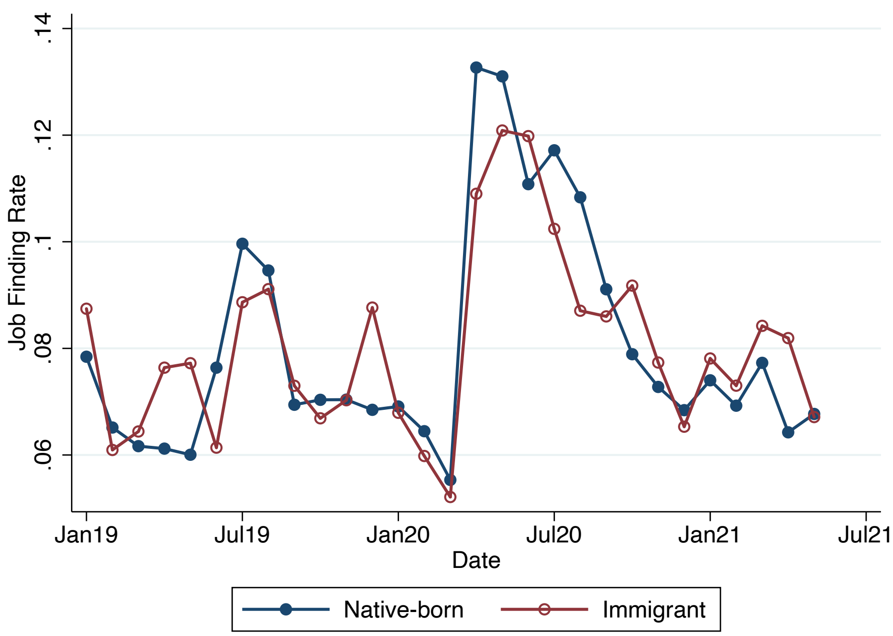
Notes: The dependent variable is set to unity if the person was "at work" or "has job, not at work last week" at time *t* but was not in that status at time *t*+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were employed in the initial period.

Figure 4. The job-finding rate, matched Basic Monthly CPS, January 2019-June 2021

A. Men



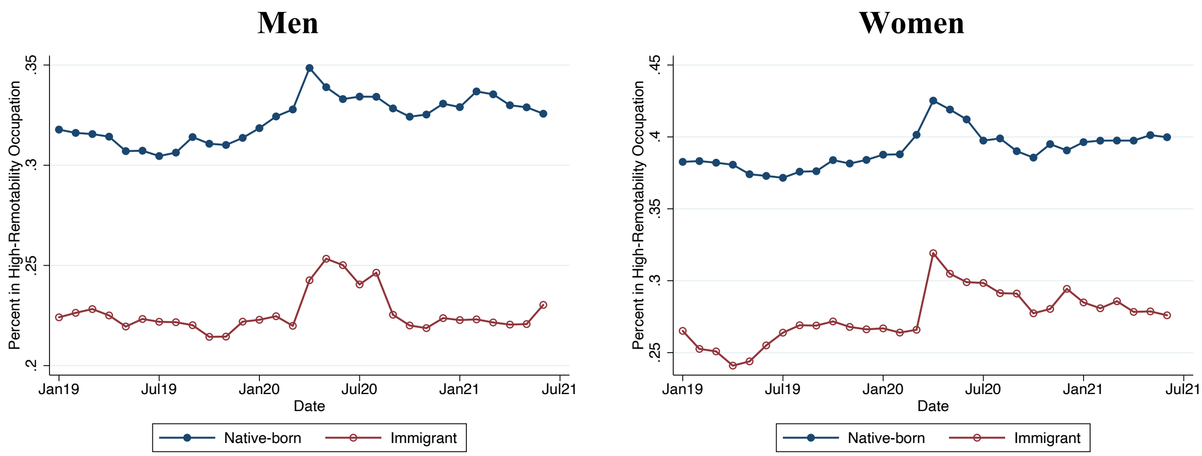
B. Women



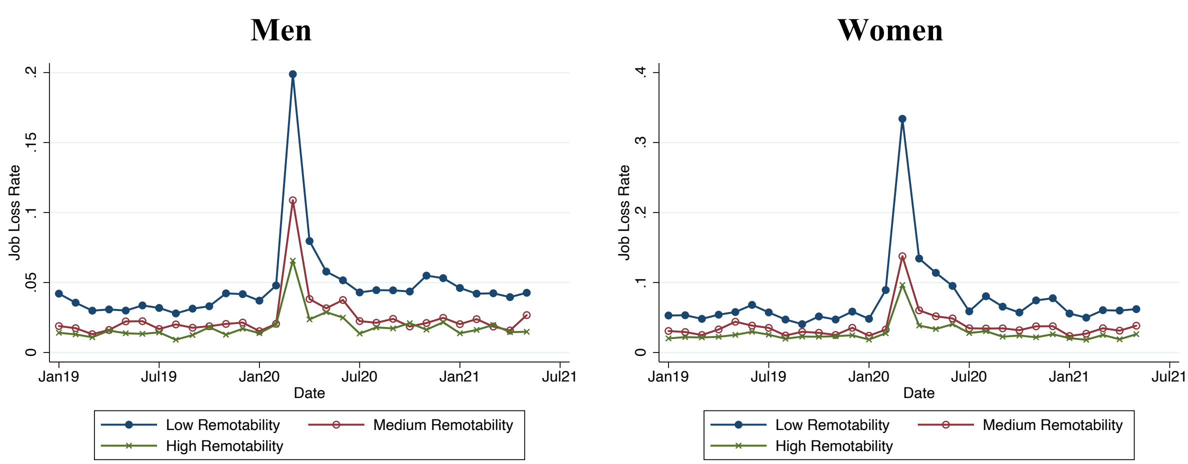
Notes: The dependent variable is set to unity if the person was not "at work" or "has job, not at work last week" at time *t* but was not in that status at time *t*+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were not employed in the initial period.

Figure 5. Job loss and the remotability of work, January 2019-June 2021

A. Share of workers employed in high-remotability jobs

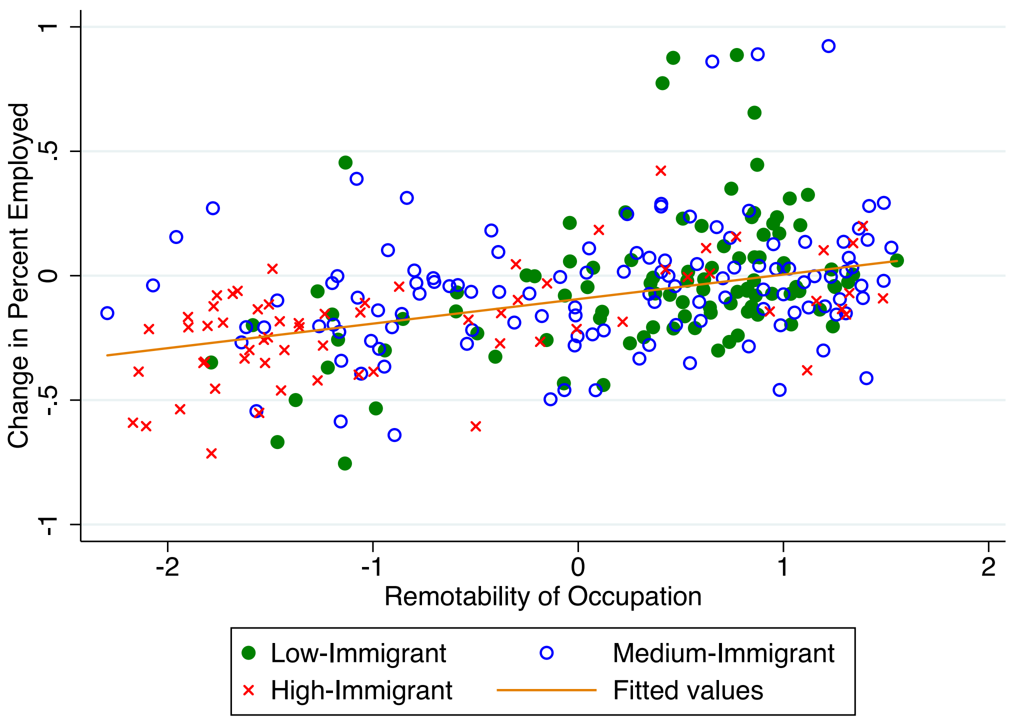


B. Job-loss rate, by degree of remotability



Notes: The remotability index uses data from O*NET to measure the ease with which a job can be performed from a remote setting; see text for details on the construction of the index.

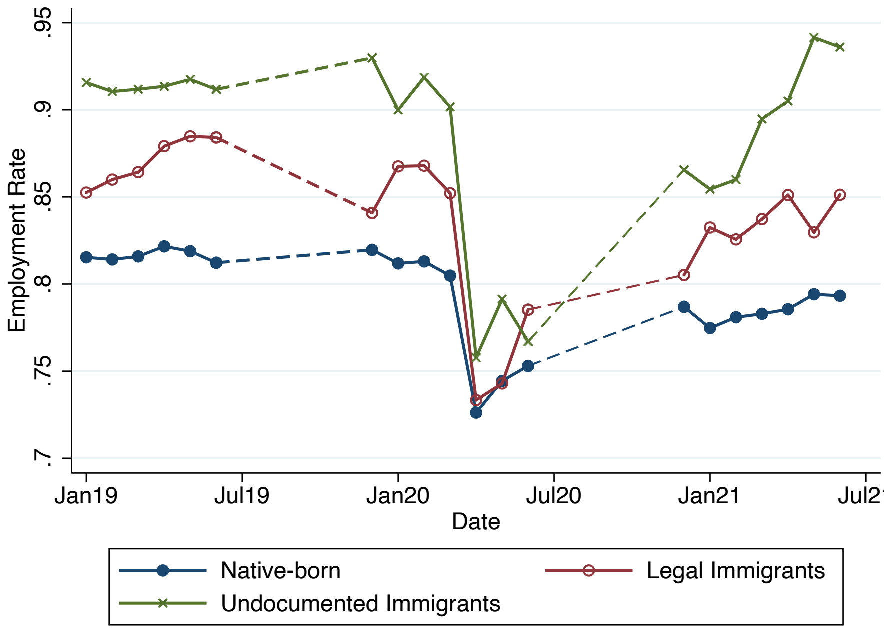
Figure 6. Employment change in early pandemic and remotability of occupation



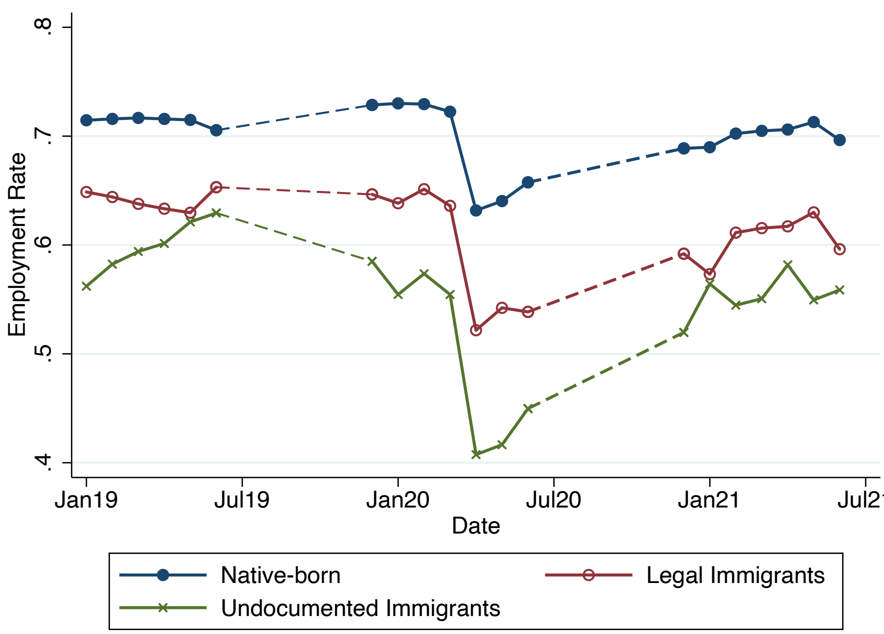
Notes: Each point represents one occupation, where the vertical axis shows the percent change in total employment in the occupation between the pre-pandemic (April-June 2019) and early pandemic (April-June 2020) periods, while the horizontal axis shows the standardized remotability index of the occupation. Occupations are classified by the share of immigrants employed in that occupation, where low-immigrant occupations are those in the bottom quintile, medium-immigrant occupations are those in the middle three quintiles, and high-immigrant occupations are those in the highest quintile. The sample consists of men and women aged 21-64. Only occupations with at least 50 workers in both periods are included, which yields a sample of 282 occupations. The weighted OLS regression line is also shown, with slope = 0.098 (0.011) and $R^2 = 0.274$.

Figure 7. Employment rate in Basic Monthly CPS by immigrant legal status, January 2019-June 2021

A. Men



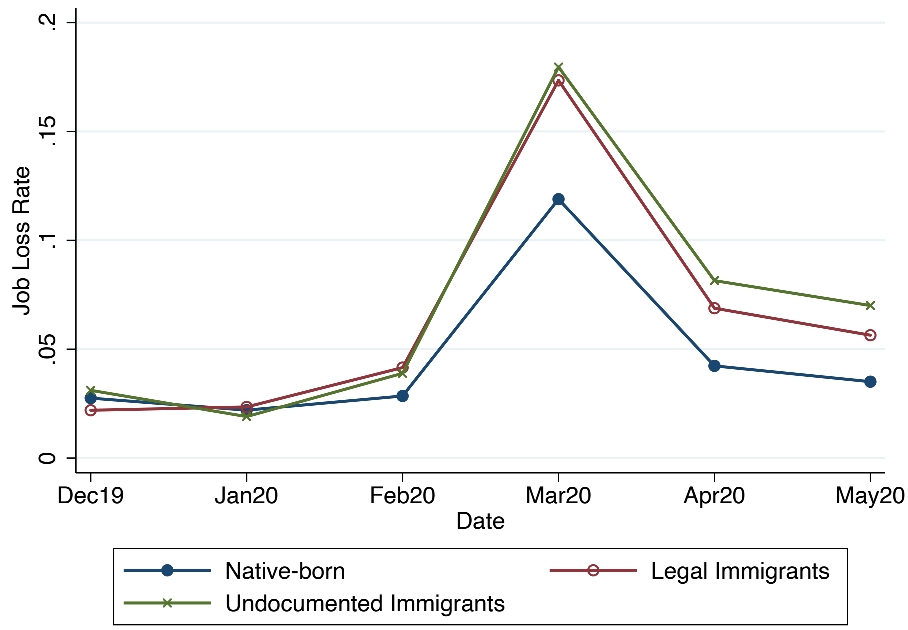
B. Women



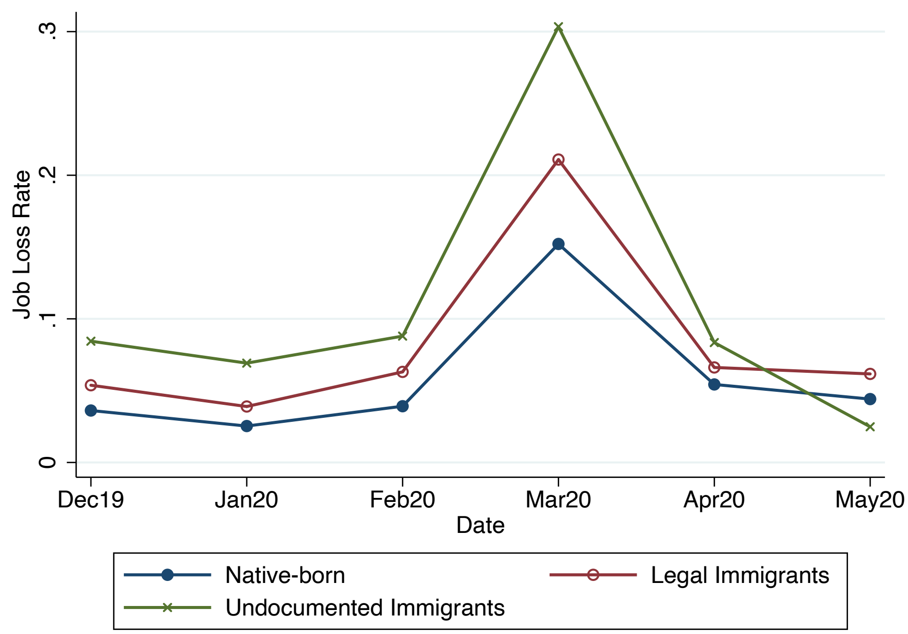
Notes: Immigrant legal status imputed for observations in the ASEC CPS using algorithm from Borjas (2017). The sample consists of persons aged 21-64 in the Basic CPS samples who are not enrolled in school and who can be matched to an ASEC supplement. Legal status cannot be imputed for respondents in the Basic CPS samples between August and November, indicated by the dashed lines. The employment rate gives the fraction of persons who are "at work" or "has job, not at work last week."

Figure 8. The job loss rate by immigrant legal status, matched Basic Monthly CPS, December 2019-May 2020

A. Men



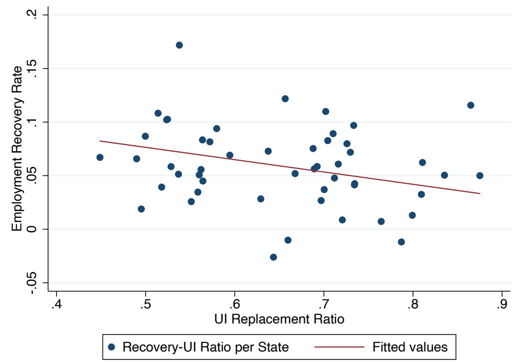
B. Women



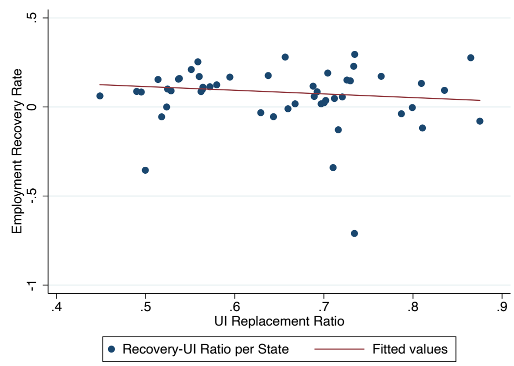
Notes: Immigrant legal status imputed for observations in the ASEC CPS using algorithm from Borjas (2017). The dependent variable is set to unity if the person was "at work" or "has job, not at work last week" at time *t* but was not in that status at time *t*+1, and zero otherwise. The sample consists of persons in the Basic Monthly files who can be matched across two consecutive months, who were employed in the initial period, and who also can be matched to an ASEC supplement.

Figure 9. Employment recovery of men and the UI replacement ratio (pooled sample of men and women)

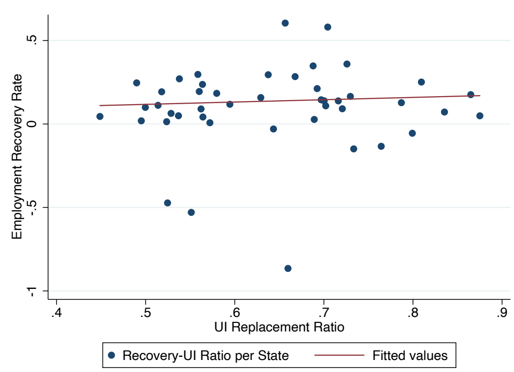
A. Natives



B. Legal immigrants



C. Undocumented immigrants



Notes: Each point represents a state, where the vertical axis shows the employment recovery of the group (natives in panel A, legal immigrants in Panel B, and undocumented immigrant in Panel C) between April-May 2020 and March-May 2021, while the horizontal axis shows the UI replacement ratio. The samples consist of persons aged 21-64 who are not in school. The weighted OLS regression lines are also shown.

Table 1. Summary statistics in pooled Basic Monthly CPS, January 2019-June 2021

	Men		Women	
	(1)	(2)	(3)	(4)
	Native	Immigrant	Native	Immigrant
Employment rate (percent)	0.775	0.829	0.688	0.584
Mean age	42.689	43.652	43.196	44.070
Education:				
Less than high school	0.062	0.227	0.047	0.200
High school graduate	0.320	0.269	0.252	0.258
Some college	0.269	0.150	0.286	0.163
College Graduate	0.350	0.354	0.415	0.379
Percent living in metro area	0.851	0.959	0.852	0.962
Percent living in:				
California	0.101	0.218	0.097	0.222
Texas	0.082	0.120	0.081	0.119
Florida	0.058	0.096	0.059	0.096
New York	0.052	0.090	0.052	0.098
Illinois	0.037	0.042	0.037	0.041
Percent living in 5 largest states	0.329	0.567	0.326	0.575
Number of observations	418,662	73,195	437,798	79,420

Notes: The sample consists of persons aged 21-64 who are not enrolled in school. The employment rate gives the fraction of persons who are "at work" or "has job, not at work last week."

Table 2. Regressions estimated in pooled CPS cross-sections, January 2019-June 2021

	Men		Women	
	(1)	(2)	(3)	(4)
Immigrant	0.067	0.064	-0.085	-0.037
	(0.003)	(0.003)	(0.004)	(0.004)
× Jan 2020	0.008	0.005	-0.010	-0.012
	(0.006)	(0.006)	(0.008)	(0.008)
× Feb 2020	0.010	0.008	-0.005	-0.004
	(0.006)	(0.006)	(0.008)	(0.008)
× March 2020	-0.006	-0.009	-0.020	-0.019
	(0.007)	(0.007)	(0.009)	(0.009)
× April 2020	-0.062	-0.062	-0.031	-0.029
	(0.009)	(0.009)	(0.010)	(0.009)
× May 2020	-0.055	-0.055	-0.039	-0.040
	(0.009)	(0.009)	(0.010)	(0.010)
× June 2020	-0.046	-0.046	-0.026	-0.026
	(0.009)	(0.009)	(0.010)	(0.010)
× July-Sept 2020	-0.018	-0.017	-0.013	-0.015
	(0.006)	(0.006)	(0.008)	(0.007)
× Oct-Dec 2020	0.002	0.004	-0.027	-0.028
	(0.006)	(0.006)	(0.008)	(0.007)
× Jan-March 2021	-0.003	-0.002	-0.021	-0.019
	(0.006)	(0.006)	(0.008)	(0.008)
× April-June 2021	-0.009	-0.006	-0.009	-0.009
	(0.006)	(0.006)	(0.008)	(0.008)
Demographics	No	Yes	No	Yes
No. of observations	857,538	857,538	904,706	904,706

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person works in the CPS reference week and zero otherwise. All specifications include a vector of calendar month fixed effects. "Demographics" indicates controls for age as a third-order polynomial, four categories of educational attainment, marital status, metro status, state fixed effects, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise.

Table 3. Panel regressions on month-to-month conditional probability of job loss (January 2019-May 2020)

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	-0.001	-0.003	-0.006	0.013	0.007	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
× February 2020	0.013	0.008	0.006	0.015	0.016	0.009
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
× March 2020	0.057	0.057	0.036	0.065	0.061	0.043
	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)
× April 2020	0.028	0.026	0.026	0.034	0.034	0.031
	(0.007)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Demographics	No	Yes	Yes	No	Yes	Yes
Industry fixed effects	No	No	Yes	No	No	Yes
Occupation fixed effects	No	No	Yes	No	Yes	Yes
No. of observations	267,587	267,587	267,587	241,646	241,646	241,646

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person was employed at time t but was not employed at time t+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were employed in the initial period. All independent variables are interacted with period fixed effects, where four periods are included: 1) pre-pandemic (Jan 2020 and earlier); 2) February 2020; 3) March 2020; and 4) April 2020. All specifications also include a vector of calendar month fixed effects. “Demographics” indicates controls for age as a third-order polynomial, four categories of educational attainment, marital status, metro status, state fixed effects, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise.

Table 4. Determinants of remotability index prior to the pandemic, January 2019-February 2020

	Men		Women	
	(1)	(2)	(3)	(4)
Immigrant	-0.324	-0.178	-0.485	-0.236
	(0.004)	(0.004)	(0.004)	(0.003)
Education				
High school graduate		0.193		0.365
		(0.005)		(0.006)
Some college		0.492		0.590
		(0.005)		(0.006)
College graduate		1.006		0.902
		(0.006)		(0.006)
Demographics	No	Yes	No	Yes
Industry fixed effects	No	Yes	No	Yes
No. of observations	351,051	351,051	318,663	318,663

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is the standardized remotability index of the worker's occupation measured so that it has a mean of zero and a standard deviation of one. The omitted education category is high school dropouts. The sample consists of persons who are employed. "Demographics" indicates controls for age as a third-order polynomial, marital status, metro status, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise. "Demographics" indicates controls for age as a third-order polynomial, four categories of educational attainment, marital status, metro status, state fixed effects, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise.

Table 5. Impact of remotability on the rate of job loss
(January 2019-December 2019 and March-April 2020)

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	-0.001	-0.004	-0.005	0.013	0.006	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
× March 2020	0.057	0.041	0.039	0.065	0.026	0.039
	(0.010)	(0.010)	(0.010)	(0.012)	(0.011)	(0.012)
Remotability		-0.009	-0.006		-0.013	-0.007
		(0.000)	(0.001)		(0.001)	(0.001)
× March 2020		-0.048	-0.034		-0.087	-0.052
		(0.003)	(0.004)		(0.005)	(0.006)
Demographics	No	No	Yes	No	No	Yes
Industry fixed effects	No	No	Yes	No	No	Yes
No. of observations	221,980	221,980	221,980	200,419	200,419	200,419

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person was employed at time t but was not employed at time t+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were employed in the initial period. All independent variables are interacted with the period fixed effect, where two periods are included: 1) pre-pandemic (January 2019-December 2020); and 2) March 2020. All specifications also include a vector of calendar month fixed effects. "Demographics" indicates controls for age as a third-order polynomial, four categories of educational attainment, marital status, metro status, state fixed effects, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise.

Table 6. Impact of immigration status on the conditional probability of job loss (January 2019-December 2019 and March-April 2020)

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Legal immigrant	-0.002	-0.003	-0.006	0.010	0.005	0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
× March 2020	0.056	0.048	0.051	0.049	0.018	0.034
	(0.011)	(0.011)	(0.011)	(0.013)	(0.012)	(0.012)
Undocumented imm.	0.002	-0.004	-0.012	0.031	0.018	0.007
	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.007)
× March 2020	0.058	0.023	0.014	0.121	0.054	0.067
	(0.018)	(0.018)	(0.018)	(0.028)	(0.027)	(0.027)
Remotability index		-0.009	-0.006		-0.012	-0.008
		(0.001)	(0.001)		(0.001)	(0.001)
× March 2020		-0.049	-0.034		-0.087	-0.051
		(0.003)	(0.004)		(0.005)	(0.006)
Demographics	No	No	Yes	No	No	Yes
Industry fixed effects	No	No	Yes	No	No	Yes
No. of observations	78,246	78,246	78,246	70,950	70,950	70,950

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person was employed at time *t* but was not employed at time *t*+1, and zero otherwise. The sample consists of persons whose immigration status can be imputed (i.e., they appeared in either the March 2019 or 2020 ASEC). who can be matched across two consecutive Basic CPS files, and were employed in the initial period. All independent variables are interacted with the period fixed effects, where two periods are included: 1) pre-pandemic (January 2019-December 2020); and 2) March 2020. All specifications also include a vector of calendar month fixed effects. "Demographics" indicates controls for age as a third-order polynomial, four categories of educational attainment, marital status, metro status, state of residence, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise.

Table 7. Differences in rate of employment recovery, by immigration status

A. Natives and Immigrants

	Men		Women	
	(1)	(2)	(3)	(4)
Spring 2021	0.054	0.054	0.072	0.071
	(0.005)	(0.005)	(0.006)	(0.005)
Immigrant	0.013	0.009	-0.133	-0.086
	(0.010)	(0.010)	(0.011)	(0.011)
× Spring 2021	0.057	0.051	0.031	0.031
	(0.013)	(0.012)	(0.015)	(0.014)
Demographics	No	Yes	No	Yes
No. of observations	49,693	49,693	52,107	52,107

B. Natives, Legal Immigrants, and Undocumented Immigrants

	Men		Women	
	(1)	(2)	(3)	(4)
Spring 2021	0.053	0.053	0.072	0.071
	(0.005)	(0.005)	(0.006)	(0.005)
Legal Immigrant	0.004	-0.009	-0.106	-0.068
	(0.011)	(0.011)	(0.012)	(0.012)
× Spring 2021	0.050	0.048	0.018	0.015
	(0.014)	(0.014)	(0.016)	(0.016)
Undocumented immigrant	0.037	0.061	-0.224	-0.147
	(0.017)	(0.017)	(0.021)	(0.021)
× Spring 2021	0.083	0.072	0.078	0.084
	(0.021)	(0.022)	(0.031)	(0.030)
Demographics	No	Yes	No	Yes
No. of observations	49,693	49,693	52,107	52,107

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person works in the CPS reference week and zero otherwise. The sample consists of persons who appeared in the April-May 2020 or March-May 2021 monthly CPS and whose immigration status can be imputed (i.e., they appeared in the March 2020 ASEC). Excludes Washington, D.C. "Demographics" indicates controls for age as a third-order polynomial, four categories of educational attainment, marital status, metro status, state fixed effects, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise.

Table 8. Predicted impact of unemployment insurance on recovery rate (pooled sample of men and women)

		Predicted recovery		
Group	Actual rate of recovery (1)	At minimum replacement ratio (2)	At mean replacement ratio (3)	At maximum replacement ratio (4)
Natives	0.063	0.081	0.063	0.034
		(0.007)	(0.004)	(0.010)
Legal immigrants	0.092	0.125	0.090	0.038
		(0.020)	(0.010)	(0.030)
Undocumented immigrants	0.139	0.111	0.134	0.169
		(0.036)	(0.018)	(0.048)

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. Column (1) shows the change in the employment rate between April-May 2020 and March-May 2021. Columns (2)-(4) show the predicted recovery rate for each group, where the unemployment replacement ratio is set to the minimum across states (column 1, ratio=0.45 in Arizona), the mean across states (column 2, ratio=0.62), and the maximum across states (column 4, ratio=0.88 in New Mexico). The predictions are made using equation (6) and the analysis excludes the District of Columbia. Employment is measured only for persons whose immigration status can be imputed (i.e., they appeared in the March 2020 ASEC). The demographic variables used to adjust employment status include controls for age as a third-order polynomial, four categories of educational attainment, marital status, metro status, state fixed effects, and an indicator variable that equals one if the respondent has at least one child under age five, and zero otherwise.